5-2012

# TWO STUDIES EVALUATING INPUT USE IN SOYBEAN AND COTTON PRODUCTION

Nathanael Mark Thompson
nthomp19@utk.edu

To the Graduate Council:

I am submitting herewith a thesis written by Nathanael Mark Thompson entitled "TWO STUDIES EVALUATING INPUT USE IN SOYBEAN AND COTTON PRODUCTION." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Agricultural Economics.

Dr. James A. Larson, Major Professor

We have read this thesis and recommend its acceptance:

Roland K. Roberts, Dayton M. Lambert, Margarita M. Velandia

Accepted for the Council:
Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

To the Graduate Council:

I am submitting herewith a thesis written by Nathanael Thompson entitled "Two Studies Evaluating Input Use in Soybean and Cotton Production." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Agricultural Economics.

James A. Larson, Major Professor

We have read this thesis
and recommend its acceptance:

Dayton M. Lambert

Roland K. Roberts

Margarita M. Velandia

Accepted for the Council

Carolyn R. Hodges
Vice Provost and Dean of the Graduate School

# TWO STUDIES EVALUATING INPUT USE IN SOYBEAN AND COTTON PRODUCTION

A Thesis

Presented for the

Masters of Science Degree

The University of Tennessee, Knoxville

Nathanael Thompson

May 2012

**Abstract**

Farmers are price takers for both inputs and outputs. Therefore, when the prices of inputs rise, as they have with many inputs used in agricultural production, optimal production practices may change. Two separate studies of the impacts of agricultural technology on input use in crop production were undertaken in this thesis. The first study evaluated economically optimal plant population considering seeding rate, maturity group, row spacing, and input-output prices in soybean production in the rolling uplands region of the upper Midsouthern United States. Data from field experiments at the University of Tennessee Research and Education Center at Milan, Tennessee during 2005, 2006, and 2007 were used to model yield response to plant population density (PPD). Given that farmers must make their planting decisions based on expected weather, original models were weighted by year based on the Ångström weather index. Evaluation of weighted average response functions found that maturity group IV soybean cultivars planted in 38 cm rows at seeding rates necessary to achieve final PPD of 115,000 plants ha$^{-1}$ would maximize farmers returns to soybean production. The second study evaluated factors influencing cotton farmers' decisions to adopt information technologies for variable-rate input application and subsequent perceptions of directional changes in the overall use of fertilizer in cotton. Data from the Cotton Incorporated 2009 Southern Precision Farming Survey were evaluated using probit models with sample selection given the sequential nature the adoption decision and farmer perceptions of directional changes in fertilizer use. Results suggest that cotton farmers in the sample who rented more of their cotton area and used picker harvest technology were more likely to perceive that overall fertilizer use declined with the use of the selected information technologies and VRT. This and other key findings of this research have

implications for a wide range of audiences ranging from University Extension to policy makers given the economic and environmental impacts.

## TABLE OF CONTENTS

## LIST OF FIGURES

**FIGURE** **PAGE**

**Chapter 2: Economically Optimal Plant Population Density in Midsouth Soybean Production**



**Chapter 3: The Adoption of Information Technologies and Subsequent Changes in Input Use in Cotton Production**

## LIST OF TABLES

**TABLE** **PAGE**

**Chapter 2: Economically Optimal Plant Population Density in Midsouth Soybean Production**



**Chapter 3: The Adoption of Information Technologies and Subsequent Changes in Input Use in Cotton Production**

# Chapter 1: Introduction

## Introduction

The prices of inputs used in crop production have been rising rapidly in the last decade. According to the United States Department of Agriculture – Economic Research Service (USDA – ERS), the average cost of seed, fertilizer, and chemicals in 2010 was 87% higher in soybean production and 95% higher in cotton production than in 1996 (USDA – ERS 2010a). In response, farmers have enhanced their effort to increase the efficiency of input use through the reevaluation of current production practices as well as the adoption of newly developed technologies. This project specifically evaluates farmer efforts to better utilize inputs in two papers by first looking at economically optimal plant population densities (EOPPD) in Midsouth soybean production and the adoption of information technologies and their subsequent effect on farmer perceptions of directional changes in input use in cotton production.

Soybean production in the United States trails only corn with 30 million hectares planted in 2011 with an estimated value of just under $36 billion (USDA – NASS 2012). Soybeans are also the leading commodity produced in the state of Tennessee with annual receipts estimated over $550 million (USDA – ERS 2010b). Soybean production in the Midsouthern United States has historically relied on the use of full-season maturity groups (MG), but yield limitations as a result of late-season drought common in the region has generated interest in earlier maturing soybean cultivars as part of an early soybean production system (ESPS) (Edwards et al. 2003; Popp et al. 2004, 2006). The use of ESPS allows soybean plants to take advantage of the region's water availability earlier in the growing season (Heatherly, Spurlock, and Elmore 2004). Because of its recent implementation in the rolling uplands of Kentucky, Tennessee, eastern Mississippi, and northern Alabama, ESPS still lacks a set of optimal production practices (Walker et al. 2010). For instance, information regarding alternative row spacing (RS) is limited for ESPS.

Soybeans planted in narrower rows at higher plant population densities (PPD) have produced higher yields as a result of better canopy development and higher light interception in the Southern United States (Boquet 1990; Bowers et al. 2000; Bullock, Khan, and Rayburn 1998; Etherege, Ashley, and Woodruff 1989; Heatherly 1988; Holshouser and Whittaker 2002; Oriade et al. 1997; Reddy 2002; Walker et al. 2010). However, these advantages have been found to be inconsistent and relatively small under nonirrigated conditions (Epler and Staggenborg 2008; Heatherly 1988; Heitholt, Farr, and Eason 2005). Economic literature has also generally supported the benefits of narrow RS in the southern United States, but available research is based on outdated input and output prices (Heatherly, Elmore, and Spurlock 2001; Reddy 2002; Oriade et al. 1997). Specifically seed has become one of the most expensive inputs in soybean production as a result of the introduction of genetically modified (GM) crops in 1996, and subsequent market concentration of the seed industry and attempts by seed companies to protect their intellectual property (Shi, Chavas, and Stiegert 2010; Rich and Renner 2007). Because both ESPS and narrower RS require higher seeding rates for optimal production, changes in the input-output price ratio directly affect farmer planting decisions.

Cotton, while not as prominent as corn or soybean, is an important crop in the Southern United States. It has an annual estimated value of $25 billion (USDA – NASS 2012), and is the sixth leading commodity in the state of Tennessee with receipts over $145 million (USDA – ERS 2010b). Cotton growers have historically applied inputs using uniform rate technology (URT), which may lead to inefficient input use in some cases as a result of variability within farm fields. Precision farming, however, allows farmers to take advantage of knowledge of in-field variability using variable rate technology (VRT), and thus increase the efficiency of input use (Roberts et al. 2004). Improved productivity of input use affords farmers using precision farming the potential for economic and environmental benefits. The factors affecting this increased productivity following VRT management have been evaluated in previous literature (Khanna 2001; Torbett et al. 2007, 2008). However, the factors affecting specific directional changes (increase, no change, or decrease) of overall input use following VRT have not been evaluated. Thus, knowledge of these factors may provide insight into the potential economic and environmental benefits of precision farming.

Two separate studies of the influence that the aforementioned agricultural technologies in soybeans and cotton have on input use were undertaken in this thesis. The objective of the first study was to determine EOPPD considering seeding rate, MG, RS, and input-output prices in the rolling uplands of the Midsouthern United States for dryland soybean production. The objective of the second study was to evaluate the farmer and farm characteristics, sources of precision farming information, and regional characteristics that influence farmer decisions to adopt selected information technologies for VRT management of inputs and the subsequent perceptions of directional changes in the use of selected inputs.

## References

Boquet, D.J. 1990. Plant Population Density and Row Spacing Effects on Soybean at Post-Optimal Planting Dates. Agronomy Journal 82(1): 59-64.

Bowers, G.R., J.L. Rabb, L.O. Ashlock, and J.B. Santini. 2000. Row Spacing in the Early Soybean Production System. Agronomy Journal 92(3): 524-531.

Bullock, D., S. Kahn, and A. Rayburn. 1998. Soybean Yield Response to Narrow Rows is Largely Due to Enhanced Early Growth. Crop Science 38(4): 1011-1016.

Economics 12(3): 326-333.

Edwards, J.T., L.C. Purcell, E.D. Vories, J.G. Shannon, and L.O. Ashlock. 2003. Short-Season Soybean Cultivars Have Similar Yields with Less Irrigation than Longer-Season Cultivars. Crop Management Online doi:10.1094/CM- 2003-0922-01-RS.

Epler, M., and S. Staggenborg. 2008. Soybean Yield and Yield Component Response to Plant Density in Narrow Row Systems. Crop Management Online doi: 10.1094/CM-2008-0925-01-RS.

Ethredge, W.J., D.A. Ashley, and J.M. Woodruff. 1989. Row Spacing and Plant Population Effects on Yield Components of Soybean. Agronomy Journal 81(6): 947-951.

Heatherly, L.G. 1988. Planting Date, Row Spacing, and Irrigation Effects on Soybean Grown on Clay Soil. Agronomy Journal 80(2): 227-231.

Heatherly, L.G., C.D. Elmore, and S.R. Spurlock. 2001. Row Width and Weed Management Systems for Conventional Soybean Plantings in the Midsouthern USA. Agronomy Journal 93(6): 1210-1220.

Heatherly, L.G., S.R. Spurlock, and C.D. Elmore. 2004. Deep and Shallow Fall Tillage for Irrigated Soybean Grown with Different Weed Management Systems in the Midsouthern USA. Agronomy Journal 96(3): 734-741.

Heitholt, J.J., J.B. Farr, and R. Eason. 2005. Planting Configuration by Cultivar Effects on Soybean Production in Low-Yield Environments. Crop Science 45(5): 1800-1808.

Holshouser, D.L., and J.P. Whittaker. 2002. Plant Population and Row Spacing Effects on Early Soybean Production Systems in the Mid-Atlantic USA. Agronomy Journal 94(3): 603-611.

Khanna, M. 2001. Sequential Adoption of Site-Specific Technologies and Its Implications for Nitrogen Productivity: A Double Selectivity Model. *American Journal of Agricultural Economics* 83(1): 35-51.

Oriade, C.A., C.R. Dillon, E.D. Vories, and M.E. Bohanan. 1997. An Economic Analysis of Alternative Cropping and Row Spacing Systems for Soybean Production. Journal of Production Agriculture 10(4): 619-624.

Popp, M.P., J.T. Edwards, L.C. Purcell, and P.M. Manning. 2004. Early-Maturing Soybean in Late-Maturing Environment: Economic Considerations. Agronomy Journal 96(6): 1711-1718.

—. 2006. Profit-Maximizing Seeding Rates and Replanting Thresholds for Soybean: Maturity Group Interactions in the Mid-South. Agricultural Systems 91(3): 211-228.

Reddy, K.N. 2002. Weed Control and Economic Comparisons in Soybean Planting Systems. Journal of Sustainable Agriculture 21(2): 21-35.

Rich, A.M., and K.A. Renner. 2007. Row Spacing and Seeding Rate Effects on Eastern Black Nightshade (Solanum Ptycanthum) and Soybean. Weed Technology 21(1):124-130.

Roberts, R.K., B.C. English, J.A. Larson, R.L. Cochran, W.R. Goodman, S.L. Larkin, M.C. Marra, S.W. Martin, W.D. Shurley, and J.M. Reeves. 2004. Adoption of Site-Specific Information and Variable Rate Technologies in Cotton Precision Farming. Journal of Agricultural and Applied Economics 36(1): 143-158.

Shi, G., J.P. Chavas, and K.W. Stiegert. 2010. Pricing of Herbicide-Tolerant Soybean Seeds: A

Torbett, J.C., R.K. Roberts, J.A. Larson, and B.C. English. 2007. Perceived Importance of Precision Farming Technologies in Improving Phosphorus and Potassium Efficiency in Cotton Production. Precision Agriculture 8(3): 127-137.

—. 2008. Perceived Improvements in Nitrogen Fertilizer Efficiency from Cotton Precision Farming. Computers and Electronics in Agriculture 64(2): 140-148.

U.S. Department of Agriculture, Economic Research Service (USDA – ERS). 2010a. *2008-2009 Costs and Returns*. Available at http://www.ers.usda.gov/Data/CostsAndReturns/ (accessed February 4, 2011).

—. 2010. *Tennessee: Leading Commodities for Cash Receipts*. 2009b. Available at http://www.ers.usda.gov/Data/FarmIncome/FIRkDMUxls.htm (accessed February 4, 2011).

U.S. Department of Agriculture, National Agricultural Statistical Service (USDA – NASS). 2012. *Crop Statistics*. Available at http://www.nass.usda.gov/Statistics_by_Subject/index.php?sector=CROPS (accessed March 5, 2012).

Walker, E.R., A. Mengistu, N. Bellaloui, C.H. Koger, R.K. Roberts, and J.A. Larson. 2010. Plant Population and Row-Spacing Effects on Maturity Group III Soybean. Agronomy Journal 102(3): 821-826.

# Chapter 2: Economically Optimal Plant Population Density in Midsouth Soybean Production

## Abstract

Traditionally grown maturity group (MG) V, and more recently adapted MG IV soybean cultivars, are subject to late-season drought conditions in the Midsouthern United States when planted in mid-May resulting in yield limitations. Thus, earlier maturing cultivars, such as MG III, have been generating interest among soybean farmers in the Midsouth. The objective of this research was to determine economically optimal plant population density (EOPPD) considering seeding rate, MG, row spacing (RS), and input-output prices in the rolling uplands region of the Midsouth for dryland soybean production. Field experiments were conducted during 2005, 2006, and 2007 at the University of Tennessee Research and Education Center at Milan, Tennessee. Maturity group III, IV, and V cultivars were planted in wide (76 cm) and narrow (38 cm) RS at a range of seeding rates from 60,000 to 593,000 seeds $ha^{-1}$ in mid-May to determine the production system that would maximize net returns. Results suggest that the profit maximizing production system was MG V soybean cultivars planted in narrow rows at seeding rates necessary to achieve a final PPD of 97,000 plants $ha^{-1}$ in 2005; MG IV soybean cultivars planted in narrow rows at seeding rates necessary to achieve a final PPD of 126,000 plants $ha^{-1}$ in 2006; and MG V soybean cultivars planted in wide rows at seeding rates necessary to achieve a final PPD of 69,000 plants $ha^{-1}$ in 2007. Given that farmers must make planting decisions based on expected weather, response functions for the three years were weighted based on the Ångström weather index. Results of the evaluation of weighted average response functions revealed that MG IV soybean cultivars planted in narrow rows at seeding rates necessary to achieve a final PPD of 115,000 plants $ha^{-1}$ would maximize returns to soybean production. Overall, results indicated that earlier maturing, MG III, soybean cultivars were never part of a production system that would maximize returns irrespective of weather conditions.

## Introduction

Soybeans are a very important crop in the United States, representing over 30 million hectares and a gross production value of nearly $36 billion in 2011 (USDA – NASS 2011b). Production practices for soybean vary by region. The upper Midsouthern United States has two distinct growing environments for soybeans: the flat landscapes of the Mississippi Delta region of Arkansas, Mississippi, and the boot heal of Missouri, which are conducive to irrigation; and the rolling uplands of Kentucky, Tennessee, eastern Mississippi, and northern Alabama, which have highly erodible soils and small field sizes that are not conducive to irrigation (Walker et al. 2010).

Soybean production in the Midsouth has historically relied on the use of full-season, maturity group (MG) V and VI cultivars given the daylength conditions in the region (Popp et al. 2006). However, the pod-fill period of these MG inconveniently coincide with the mid-June through late August drought that is common in the region subsequently limiting yield potential (Heatherly and Hodges 1999). In an effort to avoid the effects of mid or late season drought, producers have increasingly adopted the use of the early soybean production system (ESPS), in which earlier maturing soybean cultivars, such as MG 00-IV, are planted in late March or early April allowing soybean plants to take advantage of the region's water availability earlier in the growing season (Boquet 1998; Heatherly and Hodges 1999; Heatherly, Spurlock, and Elmore 2004; Popp et al. 2004). Hence, the use of MG IV cultivars has become widely adopted in the Midsouth as an alternative to MG V and VI (Hill, Popp, and Manning 2003).

However, soil moisture and temperature conditions often restrict the planting of earlier maturing cultivars to late April or early May, which consequently still subjects MG IV cultivars to mid-June drought (Edwards et al. 2003; Popp et al. 2004). For this reason, even earlier maturing cultivars, MG 00-III, have been generating interest among farmers in the Midsouth (Edwards and Purcell 2005; Edwards et al. 2003; Holshouser and Whittaker 2002; Lee, Egli, and TaKrony 2008; Popp et al. 2004, 2006; Walker et al. 2010). Edwards and Purcell (2005) found that MG II-VI soybean had similar yield potential in the Mississippi Delta region of the Midsouth, but earlier maturing cultivars generally required higher plant population density (PPD) to reach these yields. Subsequent economic analysis of these data estimated that economically optimal plant populations (EOPPD) of 490,000 plants $ha^{-1}$ for MG II to 110,000 plants $ha^{-1}$ for MG VI, generated similar net returns ranging from \$502.00 $ha^{-1}$ for MG II to \$529.00 $ha^{-1}$ for MG IV (Popp et al. 2006). The choice between these MG was said to depend on yield potential, seasonal sale price, irrigation requirement, and seed cost (Popp et al. 2006). However, one important factor not evaluated in their research was variations in row spacing (RS).

Soybeans are cultivated in a variety of RS, but in the Southern United States soybeans planted in narrower rows (<50 cm) at higher PPD have produced higher yields due to the benefits of quicker canopy closure and higher light interception (Boquet 1990; Bowers et al. 2000; Bullock, Khan, and Rayburn 1998; Etherege, Ashley, and Woodruff 1989; Heatherly 1988; Holshouser and Whittaker 2002; Oriade et al. 1997; Reddy 2002; Walker et al. 2010). However, under nonirrigated growing conditions, reported yield benefits have been relatively small and inconsistent (Epler and Staggenborg 2008; Heatherly 1988; Heitholt, Farr, and Eason 2005). Thus, RS choice cannot be based solely on yield benefits, but rather by measuring yield advantages against the economics of each system (Heatherly, Elmore, and Spurlock 2001). Oriade et al. (1997) were the first to confirm the economic benefits of narrower RS in Midsouth soybean production, evaluating three tillage by row spacing treatments. They found yields and net returns for soybeans planted in narrow RS were higher in both irrigated and nonirrigated environments. Subsequent research by Heatherly, Elmore, and Spurlock (2001) and Reddy (2002) found that yield benefits were more than enough to offset the higher costs of equipment, seed, and weed management associated with narrower RS, supporting the findings of Oriade et al. (1997).

While the aforementioned studies suggest potential economic benefits of ESPS and narrow row soybean production in the Midsouth, these potential economic benefits have not been evaluated for dryland soybean production in the rolling upland region of the Midsouthern United States.

In recent years the cost of soybean production has risen considerably. In particular, seed has become one of the most expensive inputs (Rich and Renner 2007). Much of the increase in the price of soybean seed can be attributed to the introduction of genetically modified (GM) varieties in 1996, and subsequent attempts by seed companies to protect their intellectual property (Epler and Staggenborg 2008; Shi, Chavas, and Stiegert 2010). As farmers strive to utilize seed inputs more efficiently, production decisions such as MG selection and RS must be reevaluated. Both ESPS and narrow RS require farmers to plant soybeans at higher PPD. Thus, as the relationship between input and output prices changes, optimal production decisions may also change due to their relationships with PPD.

There are many other production practices that may also affect returns to soybean production. For instance, farmers may use different planting dates as part of ESPS in an effort to avoid late-season drought (Heatherly 2005; Heatherly and Spurlock 1999; Lee, Egli, and TaKrony 2008). Earlier planting dates have generally required lower PPD to achieve EOPPD, and have consistently generated higher returns as a result of higher yields, lower costs, and higher prices received (Heatherly and Spurlock 1999; Lee, Egli, and TaKrony 2008). However, when considering earlier planting dates, farmers must also consider additional equipment and labor costs resulting from the limited number of days available for field work (Heatherly and Spurlock 1999). While it is evident that planting date plays a vital role in soybean production, it is beyond the scope of this research, which evaluated the impacts of MG, RS, and PPD on soybean profitability.

The objective of this research is to determine EOPPD considering seeding rate, MG, RS, and input-output prices in the rolling uplands region of the Midsouth for dryland soybean production. The potential to avoid late-season drought common in the Midsouth has caused growing interest in ESPS. Also, economic analysis of alternative RS recommendations are currently lacking in the Midsouth for farmers considering ESPS. In addition, rising seed prices inevitably influence these decisions, given the direct effect of MG and RS decisions on PPD. Previous research regarding EOPPD for the rolling uplands region is limited, and currently available EOPPD estimates are based on production practices different than what is evaluated in this research. Results of this study have the potential to provide farmers with information regarding seeding rate, MG selection, and RS decisions that will maximize profits.

## Methods and Procedures

### *Analytical Framework*

Farmers are assumed to be profit maximizers and price takers for their inputs and outputs (Nicholson 2005). Thus, EOPPD can be calculated by determining the PPD at which the marginal yield impact of the last additional plant is equal to its cost using the following equation:

$$(1)\ max_{i,j,k}E\left[NR(PPD_{i,j,k})\right] = p \times E\left[Y(PPD_{i,j,k})\right] - v \times PPD_{i,j,k},$$

where *E* is the expectations operator; *NR* is net returns ($ ha$^{-1}$); *PPD* is plant population density (plants ha$^{-1}$) which is determined by seeding rate *i* (seeds ha$^{-1}$), MG *j* (MG III, IV, and V), and

RS $k$ (76 and 38 cm rows); $p$ is soybean oilseed price (\$ $kg^{-1}$); $Y$ is soybean oilseed yield (kg $ha^{-1}$); and $v$ is seed cost of each additional plant (\$ $plant^{-1}$). Assuming not all seed planted will germinate to produce harvestable plants, PPD is affected by both seeding rate and the expected plant survival rate (PSR) (Larson, Roberts, and Gwathmey 2007). As a result, seed cost per plant can be calculated using the following equation:

(2) $v = r/PSR$,

where $v$ is the cost of each additional plant (\$ $plant^{-1}$), $r$ is the seed cost (\$ $seed^{-1}$), and $PSR$ is the expected plant survival rate $\epsilon(0,1)$. Hence, EOPPD can be converted to optimal seeding rates by dividing by the $PSR$. Note that up until 2002, technology fees for GM soybean were assessed directly to farmers as a fixed per hectare charge. Given the fixed nature, farmers were able to ignore this fee when making PPD decision. But in 2002, this policy changed when Monsanto started charging a royalty to seed companies rather than assessing technology fees directly to farmers (Monsanto Company 2001). Seed companies then passed this royalty along to farmers by increasing the price of seed packages. Thus, technology fees are now incorporated into the price of seed, $r$, and have a direct impact on PPD decisions.

Higher seeding rates and therefore PPD are assumed to increase net returns due to higher yields. However, at some point the cost of increasing the seeding rate will actually decrease net returns because of higher seed costs. RS is also directly related to PPD. As RS decreases, PPD increases as plants become more equidistantly placed. Narrower rows are assumed to have the benefits of quicker canopy closure, which helps preserve soil moisture and inhibit weed growth. However, at some level of RS, rows become too narrow causing competition among plants for necessary nutrients as well as lodging, both of which reduce net returns through yield reduction (Cooper and Jeffers 1984; Webber, Shibles, and Byth 1966). Based on these assumptions, profit-maximizing producers will choose the PPD that produces the highest profits compared to other PPDs.

The first-order condition for profit maximization is that marginal revenue product (*MRP*) equals marginal input cost (*MIC*) (Debertin 1986; Nicholson 2005):

$$(3)\ \frac{\partial Y}{\partial PPD_{i,j,k}} \times p = MRP = MIC = v,$$

where *Y* is the total physical product (TPP) which in this case is soybean oilseed yield (kg $ha^{-1}$); *PPD* is plant population density (plants $ha^{-1}$) which is determined by seeding rate $i$ (seeds $ha^{-1}$), MG $j$ (MG III, IV, and V), and RS $k$ (76 and 38 cm rows); $p$ is soybean oilseed price (\$ $kg^{-1}$); and *v* is seed cost of each additional plant (\$ $plant^{-1}$). Assuming the cost of each additional unit of an input is constant, *MIC* is equal to the price per unit of that input, *v*. Therefore, the EOPPD is the point where *MRP* equals *v* (Debertin 1986; Nicholson 2005). At this point, the return from the last unit of input is just equal to its cost. It is also assumed that the second order conditions for profit maximization, diminishing marginal physical product (MPP), are met (Debertin 1986; Popp et al. 2006). That is, net returns are decreasing at EOPPD.

As can be derived from the relationship between *MRP* and *MIC*, EOPPD also changes with the relationship between input cost and the output price (i.e. the *v:p* ratio) (Debertin 1986). The EOPPD is equal to the point where a line with the slope of *v*/*p* is just tangent to the TPP curve (Debertin 1986). In cases where *v* is low relative to *p*, PPD close to the EOPPD show little changes in net returns. But when *v* rises, as they have with many inputs in crop production, the ratio between *v* and *p* becomes larger, and small deviations from EOPPD cause much larger changes in net returns (Lauer and Stanger 2006). It is for this reason that knowledge of EOPPD has become increasingly important to farmers.

### *Data*

The data for this study were from field experiments during 2005, 2006, and 2007 at the University of Tennessee Research and Education Center at Milan, Tennessee (35.92° N, 88.74° W). The soil was Falaya silt loam (coarse-silty, mixed, active, acid, thermic Aeric Fluvaquents). Experimental plots were arranged in a randomized complete block, split-plot design with four replications. The main plot was cultivar and the subplot consisted of a two-factor-factorial treatment arrangement of row spacing by seeding rate (Walker et al. 2010).

In all years of the study, glyphosate-resistant MG III, IV, and V soybeans were planted in 76 and 38 cm rows. Maturity group III cultivars Asgrow 3906, Delkalb 36-52, and Pioneer 93M90 were planted at seeding rates between 247,000 and 593,000 seeds $ha^{-1}$; MG IV cultivars Pioneer 94B73 and Vigoro 42N3 were planted at seeding rates between 60,000 and 180,000 plants $ha^{-1}$; and MG V cultivar Vigero 52N3 was planted at seeding rates between 60,000 and 180,000 plants $ha^{-1}$ (see Table 2.1 for more detailed planting information). Seeds were planted using no-tillage practices in all years using a modified John Deere MaxEmerge 7240 planter (Walker et al. 2010). In each year weeds were controlled using a burndown application of glyphosate plus dicambia (3,6-dichloro-2-methoxybenzoic acid) before planting, followed by two post-emergence applications of glyphosate according to the University of Tennessee recommendations (Flinchum 2001).

Net returns to soybean yield were determined using marketing year soybean prices for the state of Tennessee from the years 2000-2010, inflated to 2011 dollars using the prices received index (PRI) (base PRI = 100 for the years 1990-1992) (USDA – NASS 2011a, 2011b). The mean soybean price in 2011 dollars was \$10.06 $bu^{-1}$, or \$0.37 $kg^{-1}$ (USDA – NASS 2011b). Average soybean seed price from University of Tennessee Extension Field Crop Budgets was \$45.00 per

140,000 seed count package (McKinley and Gerloff 2012). Selling soybean seed in seed packages has become the norm for various reasons in the last several years, one of which is the rising cost of seed (Moore 2010). It is emphasized that seed prices can vary based on seed traits, such as conventional versus GM varieties, as well as based on yield potential of the cultivar (Popp et al. 2006). Assuming a PSR of 85%, the price of each additional plant was \$0.0004 plant$^{-1}$ (McKinley and Gerloff 2012).

Total planting costs for wide rows included a 215 horsepower tractor and a base model Kinze 3500 Twin-Line® Planter (eight row, 76 cm RS, no-tillage) (Kinze Manufacturing Inc. 2011; McKinley and Gerloff 2012). Total planting costs for narrow rows included a 215 horsepower tractor, a base model Kinze 3500 Twin-Line® Planter, and the addition of a Kinze Interplant® Solid Row Package (seven offset push row planting units which enables planting in 38 cm rows) (Kinze Manufacturing Inc. 2011; McKinley and Gerloff 2012). Planting costs were annualized by creating budgets using American Society of Agricultural and Biological Engineers (ASABE) cost and returns guidelines (ASABE 2011a, 2011b). A farm size of 405 hectares was assumed, and tractor and planter prices were from University of Tennessee Extension Budgets and Kinze Manufacturing Inc. (Kinze Manufacturing Inc. 2011, McKinley and Gerloff 2012). Ownership costs for depreciation and opportunity cost of capital were estimated using an expected useful life of 12,000 hours and 1,500 hours for the tractor and planter, respectively, using the capital recovery method, and an interest rate of 6% (ASABE 2011a; McKinley and Gerloff 2012). Additional ownership costs included taxes, insurance, and housing, which were all estimated as a percentage of the purchase price (ASABE 2011a). Operating costs included repairs and maintenance of both the tractor and planter, and labor, fuel, and lubrication costs for the tractor (ASABE 2011a). Total planting equipment costs were converted to per hectare costs of \$30.78 and \$36.12 ha$^{-1}$ for wide and narrow RS, respectively.

Differences in RS may also lead to differences in fuel and labor costs. It is hypothesized that fuel cost would increase under narrower RS given the increased weight and back-force of the additional planting units, and labor cost would also increase given the additional time required to fill the extra seed hoppers. However, due to the difficulty of quantifying these changes and the expectation these changes would be rather small, fuel and labor costs are assumed constant for both wide and narrow RS.

***Empirical Models***

To evaluate EOPPD, a yield response equation as a function of PPD was estimated for each MG, RS, and year combination:

(4) $Y_{i,j,k} = f\left(PPD_{i,j,k}\right) + \varepsilon_{i,j,k}$,

where $Y$ is yield (kg ha$^{-1}$), $PPD$ is final plant population density (plants ha$^{-1}$), $i$ is seeding rate (seeds ha$^{-1}$), $j$ is MG (MG III, IV, and V), $k$ is RS (38 cm and 76 cm rows), and $\varepsilon$ is a random error term. Based on a review of agronomic literature, the relationship between PPD and soybean yield assumes diminishing marginal physical productivity of each additional plant (Holliday 1960a, 1960b; Weiss 1949). Thus, as PPD increases, soybean yield is assumed to increase at a decreasing rate. At some unknown PPD, yield is expected to either plateau or decrease as PPD is further increased. Based on these assumptions, the data were fitted to square root, quadratic, and quadratic plus plateau functional forms, all of which impose diminishing marginal physical productivity, to evaluate which best fits the data (Cox and Cherney 2011; De Bruin and Pedersen 2008; Holliday 1960a, 1960b; Popp et al. 2006). The choice between functional forms was made based on a variety of measures of goodness-of-fit including *F*-statistics and Akaike information criterion (AIC).

Because farmers cannot predict future weather conditions, they must make their planting decisions based on expected weather. Year by year analysis may provide beneficial *ex post* information, but it does not help farmers in making future planting decisions. Thus, original response equations were weighted by year based on the weighting procedure by Lambert, Lowenberg-DeBoer, and Malzer (2007) to establish response functions for each MG, RS combination that were representative of expected weather conditions. When calculating the weights, different critical periods of soybean growth were considered. The weights were calculated as a function of the weather in May through September, or the entire growing season for each year. This system was chosen due to the role weather conditions play in all phases of soybean growth (Egli 2009). While phase two of soybean growth, flowering and pod set, is considered by most to be the critical period given the detrimental effects adverse weather conditions have on yield; both phase one, vegetative growth, and phase three, seed filling, also have negative effects on yield if weather conditions are adverse (Egli 2009). Annual weights were calculated as:

$$(5)\ w_t = \prod_{l,t} \phi(A_{l,t}) / \sum_t \prod_{l,t} \phi(A_{l,t}) ,$$

where $l$ is the month (May, June, July, August, or September); $t$ is the year (2005, 2006, or 2007); $\phi(\cdot)$ is the normal probability density function; and $A$ is an Ångström weather index. The weighting plan is based on the rules of general probability products:

$$(6)\ P\left(X_1 \cap_{i\in[1,\dots,N-1]} X_i\right) = \prod_{i\in[1,\dots,N]} P(X_i) ,$$

assuming the Ångström index in month $l$ is independent of the Ångström index in month $l$–1 (Lambert, Lowenberg-DeBoer, and Malzer 2007). The Ångström weather index is a function of precipitation and temperature calculated using the following equation:

(7) $A = \frac{P}{1.07^T}$ ,

where $P$ is monthly precipitation (mm month$^{-1}$) and $T$ is the average monthly temperature (°Celsius) (Oury 1965). The Ångström index was chosen over other weather indices due to its continuous properties and the relative availability of the required data (Mooney et al. 2010; Oury 1965). Precipitation and temperature data were collected from the National Oceanic and Atmospheric Association (NOAA) for the years 1910-2010 at the Milan Experiment Station in Milan, Tennessee (NOAA 2011).

By using a partial budget, differences in net returns are able to be determined by focusing only on those costs and returns that change with alternative production practices evaluated (PPD, MG, and RS) (Lambert and Lowenberg-DeBoer 2003). Thus, seed costs and planting costs were subtracted from revenues at EOPPD using the following equation:

(8) $max_{i,j,k} E\left[NR(PPD_{i,j,k})\right] = p \times E\left[Y(PPD_{i,j,k})\right] - v \times PPD_{i,j,k} - TPC_k$,

where $E$ is the expectations operator; $NR$ is net returns (\$ ha$^{-1}$); $PPD$ is plant population density (plants ha$^{-1}$) which is determined by seeding rate $i$ (seeds ha$^{-1}$), MG $j$ (MG III, IV, and V), and RS $k$ (76 and 38 cm rows); $p$ is soybean oilseed price (\$ kg$^{-1}$); $Y$ is soybean oilseed yield (kg ha$^{-1}$); $v$ is seed cost of each additional plant (\$ plant$^{-1}$); and $TPC$ is total planting cost (\$ ha$^{-1}$). Since production costs other than seed and planting costs were assumed similar across PPD, the MG, RS combination that generated the highest net returns at EOPPD would be chosen on the basis of highest profitability.

Analysis for individual year response functions and the weighted average response functions include biologically optimal PPD (BOPPD), EOPPD, yields, and net returns. Biologically optimal PPD and EOPPD will be estimated for each MG, RS combination by differentiating equations (4) and (8) with respect to PPD, setting the first order conditions equal to zero, and solving for PPD. Plugging the estimated EOPPD back into equations (4) and (8), yields and net returns will then be estimated for each MG, RS combination.

***Hypotheses***

The hypothesized impacts on EOPPD of changes in MG and/or RS decisions are as follows. Earlier maturing cultivars are expected to require higher plant populations to reach EOPPD (Holshouser and Jones 2003; Edwards and Purcell 2005; Popp et al. 2006). Previous agronomic literature established that earlier maturing cultivars reach the first reproductive stage, "beginning bloom", sooner than later cultivars (Flinchum 2001; Lee, Egli, and TaKrony 2008). Consequently, plants are smaller and canopy development is impeded, resulting in the need for higher PPD to maximize light interception (Kane and Grabau 2002; Lee, Egli, and TaKrony 2008; Wells 1991). Soybeans planted in narrower rows are also expected to require higher plant populations to reach EOPPD (Devlin et al. 1995; Weber, Shibles, and Byth 1966). Soybean plants generally respond positively to more equidistant spacing. As row spacing decreases, increased seeding rates maximize use of space (De Bruin and Pedersen 2008).

Soybeans planted in narrow rows are expected to produce higher net returns than those planted in wider rows. The economic benefits of narrow rows are primarily driven by potential yield benefits. Again, as plant spacing becomes more equidistant, canopy development and light interception improve, generating higher yields (Shibles and Webber 1966; Webber, Shibles, and Byth 1966). Subsequently, these higher yields generally translate into higher returns to the farmer (Heatherly, Elmore, and Spurlock 2001; Reddy 2002; Oriade et al. 1997). However, increased seed costs due to higher PPD and the potential for competition among plants associated with narrower RS may limit economic benefits (Devlin et al. 1995; Elmore 1998).

Maturity group III cultivars are expected to generate the highest net returns. While the use of MG IV and V soybean cultivars are common in the Midsouth, recent literature has made a case for the agronomic benefits of planting earlier maturing cultivars in order to better avoid the common late-season drought in the region (Edwards and Purcell 2005; Popp et al. 2004, 2006; Walker et. al. 2010). However, increased seed costs due to higher PPD associated with earlier maturing cultivars may limit the economic benefits of MG III soybean cultivars (Popp et al. 2006).

***Statistical Analysis***

Equation (4) was estimated using the MODEL procedure in SAS for each MG, RS, and year combination (SAS Institute Inc. 2008). The model was fitted to square root, quadratic, and quadratic plus plateau functional forms. Goodness-of-fit criteria including *F*-statistics and AIC were used to determine which functional form best fit the yield data. Given a candidate functional form, the model was investigated for multicollinearity and heteroskedasticity. Collinearity diagnostics were determined using the COLLIN statement in SAS (SAS Institute Inc. 2008). Multicollinearity occurs when two or more independent variables are highly correlated with each other (Chatterjee and Price 1991). Due to the nature of the functional forms used in this analysis, some degree of multicollinearity is expected. If present, multicollinearity causes standard errors to be inflated, which in turn can affect the significance and inferential power of coefficients (Chatterjee and Price 1991). Heteroskedastic-consistent covariance matrix estimation was used following the procedure proposed by White (1980) using the PROC

MODEL HCCME=1 statement (SAS Institute Inc. 2008). Heteroskedasticity occurs when the variance of the error term of the regression is not constant (Wooldridge 2009). If present, heteroskedasticity causes estimates of variance, and therefore standard errors, to be over or under represented. This also leads to biased inference with respect to hypothesis tests (Wooldridge 2009).

The model was further evaluated using the ESTIMATE and TEST statements in the PROC MODEL command (SAS Institute Inc. 2008). The ESTIMATE statement computes values for nonlinear functions (e.g., the net revenue function) that include parameters fitted in the model (SAS Institute Inc. 2008). Estimated values calculated using this statement are presented with standard errors and *t*-values. This statement was used for estimating BOPPD, EOPPD, yields, and net returns as well as weighting regression coefficients. The TEST statement performs tests of nonlinear hypotheses on model parameters (SAS Institute Inc. 2008). The default Wald statistic, interpreted based on the chi-squared distribution, was used for this analysis (SAS Institute Inc. 2008). Hypotheses for differences in BOPPD and EOPPD, as well as differences in net returns among each MG, RS combination were tested using this statement.

## Results

### *Model Evaluation*

For each functional form, 18 response equations were estimated; one for each MG, RS, and year combination. The quadratic functional form was determined to best fit the data on the basis of visual inspection, *F*-statistic, and AIC. Results from the estimated yield response functions can be seen in Table 2.2. Of the 18 original response equations, eight were found to be significant at the 10% level based on model *F*-tests. One of which, MG III planted in 76 cm RS in 2005, did not display the expected concave properties of the quadratic function. In addition, two of the remaining response functions that were not significant, MG IV planted in 38 and 76 cm RS in 2007, also did not display the expected concave properties. For these functions, net returns were estimated for both the minimum and maximum observed PPD, and the one that generated higher net returns was presented as the EOPPD.

Annual equations were then weighted by year to calibrate the response functions to expected weather conditions. Weather data for the three years of the experiment, and the 100 year average can be found in Table 2.3. Weights were 0.14, 0.71, and 0.15 for the years 2005, 2006, and 2007 respectively. As probability theory suggest, the weights for the three years sum to one. Further understanding of what these weights represent is realized by looking at weather conditions in each of the three years and comparing the Ångström indices with their 100 year averages. The 2005 response functions received the lowest weight of the three years as a result of close to average monthly temperatures, but considerably high precipitation in June, July, and August. The 2006 response functions received the highest weight because weather conditions were similar to the 100 year average for the entire growing season. Lastly, the 2007 response function received another relatively low weight as a result of what was recorded as severe drought conditions due to higher than average temperatures and major deficits in precipitation in May, July, and August (Fuchs 2008). Weights were applied ($\sum_t w_t \beta_{i,t}$) by year, $t$, reducing the original 18 response equations to six weighted average response equations, one for each MG, RS combination. Weighted coefficients can be seen in Table 2.4. All weighted response functions possessed the expected concave properties of the quadratic function, and three of them showed significance at the 5% level on each the estimated intercept, linear, and squared coefficients.

*2005 Growing Season*

Results from the evaluation of the 2005 soybean yield response functions can be seen in Table 2.5. All estimated BOPPD and EOPPD fell within the observed PPD of the experiment. Economically optimal PPD for wide and narrow RS were 349,000 and 198,000; 102,000 and 60,000; and 44,000 and 97,000 plants ha$^{-1}$ for MG III, IV, and IV respectively. Net returns for soybeans planted in narrow RS were \$114, \$210, and \$240 ha$^{-1}$ higher than those planted in wide RS for MG III, IV, and V cultivars respectively. When evaluating MG selection, MG V cultivars generated the highest returns for both wide and narrow RS. Thus, for the 2005 growing season MG V soybean cultivars, planted in 38 cm RS resulted in the highest returns to soybean production. Given the ample water supply that was available during the entire 2005 growing season, these results suggest that traditionally grown MG V cultivars generate higher returns compared to earlier maturing cultivars when water is not limited by drought late in the growing season.

*2006 Growing Season*

Results from the evaluation of the 2006 soybean yield response functions can be seen in Table 2.6. All estimated BOPPD and EOPPD fell within the observed PPD of the experiment. Economically optimal PPD for wide and narrow RS were 370,000 and 390,000; 84,000 and 126,000; and 49,000 and 92,000 plants ha$^{-1}$ for MG III, IV, and V respectively. Net returns for soybeans planted in narrow RS were \$113, \$168, and \$71 ha$^{-1}$ higher than those planted in wide RS for MG III, IV, and V respectively. When evaluating MG selection, MG IV cultivars generated the highest returns for both wide and narrow RS. Thus, for the 2006 growing season MG IV soybean cultivars, planted in 38 cm RS resulted in the highest returns to soybean production.

*2007 Growing Season*

Results from the evaluation of the 2007 soybean yield response functions can be seen in Table 2.7. All estimated BOPPD and EOPPD fell within the observed PPD of the experiment. Economically optimal PPD for wide and narrow RS were 134,000 and 236,000; 121,000 and 179,000; and 69,000 and 70,000 plants ha$^{-1}$ for MG III, IV, and V respectively. Net returns for soybeans planted in narrow RS were \$17 ha$^{-1}$ higher than those planted in wide RS for MG IV cultivars. Net returns for MG III and V soybean cultivars planted in wide RS were \$16 and \$40 ha$^{-1}$ higher respectively than those planted in narrow RS. When evaluating MG selection, MG V cultivars generated the highest returns for both wide and narrow RS. Thus, for the 2007 growing season MG V soybean cultivars, planted in 76 cm RS resulted in the highest returns to soybean production. Given the drought conditions during the 2007 growing season, these results support the findings of Alessi and Power (1982) and Taylor (1980) that the benefits of narrow RS may dissipate in years of extreme water stress.

***Weighted Average Response Functions***

Results from the analysis of the weighted average response functions can be seen in Table 2.8. Estimated BOPPD for all MG, RS combinations except one fell within the observed PPD of the experiment. As is common practice, instead of presenting a plant population out of the range of the experiment, the BOPPD for this MG, RS combination is presented at the highest observed PPD for that experiment. All of the estimated EOPPD fell within the PPD observed in the experiment. Economically optimal PPD were lower than BOPPD for all MG, RS combinations.

Evaluating EOPPD by RS, generally EOPPDs were found to be higher for soybeans planted in narrower rows as expected. MG IV and V cultivars both reached EOPPD at higher plant populations for soybeans planted in 38 cm rows than those planted in 76 cm rows. However, EOPPD for MG III cultivars were approximately 84,000 plants $ha^{-1}$ lower for soybeans planted in 38 cm rows. The cause for this result is likely the strong convex shape of the original 2005, MG III, 76 cm RS response equation. As previously discussed, the weighting scheme moderated the convexity, but large original coefficients caused the shape of the weighted average MG III, 76 cm RS response function to be very flat which led to higher EOPPD.

Holding RS constant, it is also evident that, as expected, earlier maturing cultivars require higher plant populations to reach EOPPD. The earliest maturing cultivars in this experiment, MG III, displayed considerably higher EOPPD than the two later maturing cultivars in the study. The estimated EOPPD of approximately 296,000 plants $ha^{-1}$ is close to the EOPPD estimated by Popp et al. (2006) of 280,000 plants $ha^{-1}$ for MG III cultivars planted in narrow rows. MG IV cultivars reached their EOPPD at considerably lower plant populations of 87,000 and 115,000 plants $ha^{-1}$ for wide and narrow RS respectively, and MG V cultivars reached their EOPPD at modestly lower levels of 51,000 and 90,000 plants $ha^{-1}$ for wide and narrow RS respectively.

Following this preliminary analysis of estimated BOPPD and EOPPD, the null hypothesis that BOPPD were equal to EOPPD for each MG, RS combination was tested. Four of the six MG, RS combinations rejected this hypothesis at the 10% level of significance. These findings generally support the hypothesis that the increase in the input-output price ratio has caused EOPPD to become significantly different from BOPPD. Three of the four MG, RS combinations that rejected the null hypotheses were for soybeans planted in 38 cm rows. Therefore, for soybeans planted in narrower rows, EOPPD were generally different from BOPPD; but for soybeans planted in wider rows there was insufficient evidence to support this hypothesis.

Net returns were calculated for each MG, RS combination (Table 2.8). Results suggest that MG IV cultivars planted in 38 cm RS generated the highest net returns, while MG III cultivars planted in 76 cm RS generated the lowest net returns of the MG, RS combinations evaluated. To better understand these results, net returns were evaluated by MG and RS separately. Putting these two factors together, the overall production system that maximized returns was evaluated. Further evaluation of differences in net returns was conducted by testing the null hypothesis that net returns for each MG, RS combination was equal to the net returns of all other MG, RS combinations. The results of these comparisons can be seen in Table 2.9, and are referred to throughout the following discussion.

Evaluating differences in net returns by RS, soybeans planted in narrow rows generated net returns of \$105, \$135, and \$75 ha$^{-1}$ higher than soybeans planted in 76 cm rows for MG III, IV, and V respectively. These results suggest that the yield benefits of narrower rows are more than enough to offset higher seed cost. Results testing for statistical differences in net returns rejected the null hypotheses at the 10% level that the net returns for soybeans planted in wide and narrow rows were equal for all MG evaluated. These findings are consistent with Oriade et al. (1997); Heatherly, Elmore, and Spurlock (2001); and Reddy (2002) that showed soybeans planted in narrow rows consistently generate higher returns to soybean production in the Midsouth. Further, plotting net returns over the range of PPD observed in the experiment, breakeven plant populations between wide and narrow RS can be evaluated (Figure 2.1). These points represent plant populations at which farmers would be indifferent between planting soybeans in wide or narrow rows. MG III cultivars had breakeven PPDs of 64,107 and 479,104 plants ha$^{-1}$. At PPDs below 64,107 and above 479,104 plants ha$^{-1}$, soybeans planted in 76 cm rows produced higher net returns. At PPDs between 64,107 and 479,104 plants ha$^{-1}$ soybeans planted in 38 cm rows generated higher net returns. MG IV cultivars evaluated in this study did not exhibit a breakeven PPD. Net returns were higher for soybeans planted in 38 cm rows for all observed PPDs. At PPD between 18,000 and 20,000 plants $ha^{-1}$, there was only a difference of about \$65.00 $ha^{-1}$ in net returns between the wide and narrow RS, but as PPD increased beyond 20,000 plants $ha^{-1}$ the difference in net returns grew substantially. The breakeven PPD for MG V cultivars was 57,634 plants $ha^{-1}$. Net returns were higher for soybeans planted in 76 cm rows at PPDs below 57,634 plants $ha^{-1}$, and at PPDs above that point net returns were higher for soybeans planted in 38 cm rows.

Evaluating differences in net returns by MG, MG IV cultivars generated the highest returns for soybeans planted in both wide and narrow RS. While it was hypothesized that earlier maturing MG III cultivars would produce higher net returns based on their ability to mature before the late-season drought that is common in the Midsouth, the results of this analysis suggest otherwise. Maturity group IV cultivars generated net returns that were more than \$100 $ha^{-1}$ higher than MG III cultivars for both 76 and 38 cm RS. In addition, the significance of differences in net returns among MG can be further evaluated by looking at the results of the side-by-side comparisons (Table 2.9). For soybeans planted in narrows rows, tests rejected the null hypotheses that net returns of MG IV cultivars were equal to the net returns of both MG III and V cultivars at the 1% level, but failed to reject the null hypothesis that net returns for MG III and V were equivalent. These results support the use of MG IV cultivars rather than MG III cultivar soybeans in narrow RS in the Midsouth for the years analyzed. Looking at soybeans planted in wide rows, the null hypothesis that net returns for MG IV cultivars were equal to the net returns for MG III was rejected at the 5% level, but the null hypotheses that MG V cultivars were significantly different from MG III or IV could not be rejected. These results do not unambiguously support the use of MG IV cultivars when planting soybeans in wide rows given the inability to determine statistical differences in net returns for MG IV and V cultivars.

Combing these findings, the overall production system that produced the highest net returns in this research was the planting of MG IV cultivars in 38 cm RS at seeding rates appropriate to achieve final PPD of approximately 115,000 plants $ha^{-1}$. While there are clearly many factors that could be considered but are beyond the scope of the present research, the results of this analysis suggest the use of a production system at least similar to the one presented.

**Summary and Conclusions**

The objective of this research was to determine EOPPD considering seeding rate, MG, RS, and input-output prices in the rolling uplands region of the Midsouthern United States for dryland soybean production. The opportunity to avoid late-season drought common in the Midsouth has caused growing interest into ESPS and earlier maturing soybean cultivars. Also, economic analysis of alternative RS recommendations are currently lacking in the Midsouth. Rising seed prices also warrant reevaluation of these practices, given the direct effect of MG and RS decisions on PPD. Yield response equations as a function of PPD were developed for each MG, RS, and year combination using data from experiments conducted for 2005 to 2007 at the University of Tennessee Research and Education Center at Milan, Tennessee. Given that farmers must make their planting decisions on the basis of expected weather conditions, the annual response functions were weighted by year based on the Ångström weather index, resulting in weighted average response functions for each MG, RS combination. Not only were these equations assumed to be representative of expected weather conditions, but they also all met the first and second order conditions for profit maximization. Lastly, using partial budgeting, a net return equation was estimated to analyze the MG, RS combination that would maximize returns to soybean production.

Initial results suggest that the combination of production practices that maximized net returns varied by year. Practices that maximized net returns in 2005 were MG V soybean cultivars planted in 38 cm RS at seeding rates necessary to achieve final PPD of 97,000 plants $ha^{-1}$; MG IV cultivars planted in 38 cm RS at seeding rates necessary to achieve final PPD of 126,000 plants $ha^{-1}$ in 2006; and MG V cultivars planted in 76 cm RS at seeding rates necessary to achieve final PPD of 69,000 plants $ha^{-1}$ in 2007. Based on what is known about weather conditions in the three years of the experiment, inference about these findings are as follows: in 2005 traditionally grown MG V cultivars out performed earlier maturing cultivars when late-season drought did not impede soybean development; in 2006 when conditions were relatively typical for the region, MG IV cultivars generated the highest returns which may imply benefits to ESPS; and results from 2007 are consistent with previous finding that the benefits of narrow RS may dissipate in years of extreme water stress.

Analysis of the weighted average response functions estimated EOPPD for wide and narrow RS of approximately 380,000 and 296,000 plants $ha^{-1}$; 87,000 and 115,000 plants $ha^{-1}$; and 51,000 and 90,000 plants $ha^{-1}$ for MG III, IV, and V respectively. Estimated EOPPD are close to currently available recommendations for MG III, but considerably lower for MG IV and V soybean cultivars in the Midsouth. Findings also generally support hypotheses that higher PPD are required to achieve EOPPD for soybeans planted in narrower RS and for earlier maturing cultivars.

It was hypothesized that MG III soybean cultivars planted in narrow RS would generate the highest returns to soybean production in the Midsouth. However, results suggest MG IV soybean cultivars planted in narrow RS generated the highest net returns of all MG, RS combinations evaluated in this research. These findings support the hypothesis of economic benefits of narrow RS, but fail to support the benefits of planting earlier maturing MG III soybean cultivars to avoid late season drought. While MG IV cultivars out yielded MG III, the cost of achieving higher PPD associated with earlier maturing cultivars also likely influenced these findings.

One consideration when interpreting the results of this study is the limitation of the conventional mid-May planting dates used for all three MG evaluated. Earlier March or April planting dates have been incorporated as part of ESPS in an effort to avoid late-season drought (Heatherly 2005; Heatherly and Spurlock 1999; Lee, Egli, and TaKrony 2008). These earlier planting dates have generally required lower PPD to achieve EOPPD, and have consistently generated higher returns as a result of higher yields, lower costs, and higher prices received (Heatherly and Spurlock 1999; Lee, Egli, and TaKrony 2008). Modeling the potential influence of planting dates on the economically optimal production system was beyond the scope of this study. However, data for alternative planting dates are available for this production region, and are an objective of future research to determine how this may affect farmer production decisions including PPD, MG, and RS.

## References


American Society of Agricultural and Biological Engineers (ASABE). 2011a. *Agricultural and Machinery Management*. ASAE D497.7. ASABE St. Joseph, MI.

—. 2011b. *Agricultural and Machinery Management*. ASAE EP496.3. ASABE St. Joseph, MI.

Boquet, D.J. 1998. Yield and Risk Utilizing Short-Season Soybean Production in the Mid-Southern USA. *Crop Science* 38(4): 1004-1011.

—. 1990. Plant Population Density and Row Spacing Effects on Soybean at Post-Optimal Planting Dates. *Agronomy Journal* 82(1): 59-64.

Bowers, G.R., J.L. Rabb, L.O. Ashlock, and J.B. Santini. 2000. Row Spacing in the Early Soybean Production System. *Agronomy Journal* 92(3): 524-531.

Bullock, D., S. Kahn, and A. Rayburn. 1998. Soybean Yield Response to Narrow Rows is Largely Due to Enhanced Early Growth. *Crop Science* 38(4): 1011-1016.

Chatterjee, S., and B. Price. 1991. *Regression Analysis by Example.* New York: Wiley.

Cooper, R.L., and D.L. Jeffers. 1984. Use of Nitrogen Stress to Demonstrate the Effect of Yield Limiting Factors on the Yield Response of Soybean to Narrow Row Systems. *Agronomy Journal* 76(2): 257-259.

Cox, W.J., and J.H. Cherney. 2011. Growth and Yield Responses of Soybean to Row Spacing and Seeding Rate. *Agronomy Journal.* 103(1): 123-128.

De Bruin, J.L., and P. Pedersen. 2008. Effect of Row Spacing and Seeding Rate on Soybean Yield. *Agronomy Journal* 100(3): 704-710.

Debertin, D.L. 1986. *Agricultural Production Economics.* New York: Macmillan Publishing Company.

Delvin, D.L., D.L. Fjell, J.P. Shroyer, W.B. Gordon, B.H. Marsh, L.D. Maddux, V.L. Martin, and S.R. Duncan. 1995. Row Spacing and Seeding Rates for Soybean in Low and High-Yielding Environments. *Journal of Production Agriculture* 8(2): 215-222.

Edwards, J.T., and L.C. Purcell. 2005. Soybean Yield and Biomass Responses to Increasing Plant Population Among Diverse Maturity Groups. *Crop Science* 45(5): 1770-1777.

Edwards, J.T., L.C. Purcell, E.D. Vories, J.G. Shannon, and L.O. Ashlock. 2003. Short-Season Soybean Cultivars Have Similar Yields with Less Irrigation than Longer-Season Cultivars. *Crop Management Online* doi:10.1094/CM- 2003-0922-01-RS.

Egli, D.B. 2009. Critical Growth Stages for Maximum Soybean Yield. *University of Kentucky Extension Corn and Soybean News* 9(5): 5-6.

Elmore, R.W. 1998. Soybean Cultivar Responses to Row Spacing and Seeding Rates in Rainfed And Irrigated Environments. *Journal of Production Agriculture* 11(3): 326-331.

Epler, M., and S. Staggenborg. 2008. Soybean Yield and Yield Component Response to Plant Density in Narrow Row Systems. *Crop Management Online* doi: 10.1094/CM-2008-0925-01-RS.

Ethredge, W.J., D.A. Ashley, and J.M. Woodruff. 1989. Row Spacing and Plant Population Effects on Yield Components of Soybean. *Agronomy Journal* 81(6): 947-951.

Flinchum, W.T. 2001. Soybean Production in Tennessee. University of Tennessee Agricultural Extension Service #PB1608.

Heatherly, L.G. 1988. Planting Date, Row Spacing, and Irrigation Effects on Soybean Grown on Clay Soil. *Agronomy Journal* 80(2): 227-231.

—. 2005. Soybean Development in the Midsouthern USA Related to Date of Planting and Maturity Classification. *Crop Management Online* doi: 10.1094/CM-2005-0421-01-RS.

Heatherly, L.G., and H.F. Hodges. 1999. *Soybean Production in the Midsouth.* Boca Raton: CRC Press LLC.

Heatherly, L.G., and S.R. Spurlock. 1999. Yield and Economics of Traditional and Early Soybean Production Systems (ESPS) Seedings in the Midsouthern United States. *Field Crops Research* 63(1): 35-45.

Heatherly, L.G., C.D. Elmore, and S.R. Spurlock. 2001. Row Width and Weed Management Systems for Conventional Soybean Plantings in the Midsouthern USA. *Agronomy Journal* 93(6): 1210-1220.

Heatherly, L.G., S.R. Spurlock, and C.D. Elmore. 2004. Deep and Shallow Fall Tillage for Irrigated Soybean Grown with Different Weed Management Systems in the Midsouthern USA. *Agronomy Journal* 96(3): 734-741.

Heitholt, J.J., J.B. Farr, and R. Eason. 2005. Planting Configuration by Cultivar Effects on Soybean Production in Low-Yield Environments. *Crop Science* 45(5): 1800-1808.

Hill, J., M. Popp, and P. Manning. 2003. Focus Group Survey Results: Typical Arkansas Crop Producer Production and Marketing Practices. Res. Rep. 971. University of Arkansas Experiment Station, Fayetteville.

Holliday, R. 1960a. Plant Population and Crop Yield: Part I. *Field Crop Abstracts* 13(3): 159-167.

—. 1960b. Plant Population and Crop Yield: Part II. *Field Crop Abstracts* 13(4): 247-254.

Holshouser, D.L., and B.P. Jones. 2003. Early-Maturing Double-Crop Soybeans Requires Higher Plant Population to Meet Leaf Area Requirements. *Crop Management Online* doi: 10.1094/CM-2003-0408-01-RS.

Holshouser, D.L., and J.P. Whittaker. 2002. Plant Population and Row Spacing Effects on Early Soybean Production Systems in the Mid-Atlantic USA. *Agronomy Journal* 94(3): 603-611.

Kane, M.V., and L.J. Grabau. 1992. Early Planted, Early Maturing Soybean Cropping System: Growth, Development and Yield. *Agronomy Journal* 84(5): 769-773.

Kinzi Manufacturing Inc. 2011. *3500 Twin-Line® Planter.* Available at http://www.kinze.com/plantersAndCarts/viewPlanter.html?id=3 (accessed August 6, 2011).

Lambert, D.M., and J. Lowenberg-DeBoer. 2003. Economic Analysis of Row Spacing for Corn and Soybean. *Agronomy Journal* 95(3): 564-573.

Lambert, D.M., J. Lowenberg-DeBoer, and G. Malzer. 2007. Managing Phosphorous Soil Dynamics Over Space and Time. *Agricultural Economics* 37(1): 43-53.

Larson, J.A., R.K. Roberts, and C.O. Gwathmey. 2007. Herbicide-Resistant Technology Price Effects on the Plant Density Decision for Ultra-Narrow-Row Cotton. *Journal of Agriculture and Resource Economics* 32(2): 383-410.

Lauer, J., and T. Stranger. 2006. Guidelines for Managing Corn Seed Costs. Agron. Dept. Field Crops 28.424-44, University of Wisconsin.

Lee, C.D., D.B. Egli, and D.M. TeKrony. 2008. Soybean Response to Plant Population at Early and Late Planting Dates in the Mid-South. *Agronomy Journal* 100(4): 971-976.

McKinley, T.L., and D.C. Gerloff. 2012. Field Crop Budgets for 2012. University of Tennessee Extension Publication AE12-05.

Monsanto Company. Monsanto Announces Simpler Pricing for Biotech Traits in 2001. Monsanto Company Press Release, St. Louis, MO, 14, June 2001. Available at http://www.biotech-infor.net/simpler_pricing.html (accessed March 9, 2012).

Mooney, D.F., R.K. Roberts, B.C. English, J.A. Larson, and D.D. Tyler. 2010. Is Switchgrass Yield Response to Nitrogen Fertilizer Dynamic? Implications for Profitability and Sustainability at the Farm Level. Paper presented at the Southern Agricultural Economic Association Annual Meeting, Orlando, FL, 6-9 February.

Moore, M. 2010. Buying Seed by Weight or Count. *Farm Industry News,* available at http://farmindustrynews.com/soybean-varieties/buying-seed-weight-or-count (accessed December 1, 2011).

Nicholson, W. 2005. Microeconomic Theory: Basic Principles and Extensions. Mason: Thomas/South-Western.

Oriade, C.A., C.R. Dillon, E.D. Vories, and M.E. Bohanan. 1997. An Economic Analysis of Alternative Cropping and Row Spacing Systems for Soybean Production. *Journal of Production Agriculture* 10(4): 619-624.

Oury, B. 1965. Allowing for Weather in Crop Production Model Building. *Journal of Farm Economics* 47(2): 270-283.

Popp, M.P., J.T. Edwards, L.C. Purcell, and P.M. Manning. 2004. Early-Maturing Soybean in Late-Maturing Environment: Economic Considerations. *Agronomy Journal* 96(6): 1711-1718.

—. 2006. Profit-Maximizing Seeding Rates and Replanting Thresholds for Soybean: Maturity Group Interactions in the Mid-South. *Agricultural Systems* 91(3): 211-228.

Reddy, K.N. 2002. Weed Control and Economic Comparisons in Soybean Planting Systems. *Journal of Sustainable Agriculture* 21(2): 21-35.

Rich, A.M., and K.A. Renner. 2007. Row Spacing and Seeding Rate Effects on Eastern Black Nightshade (Solanum Ptycanthum) and Soybean. *Weed Technology* 21(1):124-130.

SAS Institute Inc. 2008. *SAS/ETS 9.2 Users Guide*. Cary, N.C: SAS Institute Inc.

Shi, G., J.P. Chavas, and K.W. Stiegert. 2010. Pricing of Herbicide-Tolerant Soybean Seeds: A Market-Structure Approach. The Journal of Agrobiotechnology Management and *Economics* 12(3): 326-333.

Shibles, R.M., and C.R. Webber. 1966. Interception of Solar Radiation and Dry Matter Production by Various Soybean Planting Patterns. *Crop Science* 6(1): 55-60.

United States Department of Agriculture, National Agricultural Statistics Service (USDA – NASS). 2011a. Price Program: History, Concepts, Methodology, Analysis, Estimates, and Dissemination. Available at http://www.nass.usda.gov/Surveys/Guide_to_NASS_Surveys/Prices/Price_Program_Methodology_v10.pdf (accessed October 10, 2011).

—. 2011b. Quick Stats 2.0. Available at http://quickstats.nass.usda.gov/ (accessed October 10, 2011).

United States Department of Commerce – National Oceanic and Atmospheric Administration (NOAA). 2011. *DATA.* Available at http://www.noaa.gov/index.html (accessed November 30, 2011).

Walker, E.R., A. Mengistu, N. Bellaloui, C.H. Koger, R.K. Roberts, and J.A. Larson. 2010. Plant Population and Row-Spacing Effects on Maturity Group III Soybean. *Agronomy Journal* 102(3): 821-826.

Webber, C.R., R.M. Shibles, and D.E. Byth. 1966. Effect of Plant Population and Row Spacing on Soybean Development and Production. *Agronomy Journal* 58(1): 99-100.

Weiss, M.G. 1949. Soybeans. *Advances in Agronomy* 1(1): 78-157.

Wells, R. 1991. Soybean Growth Response to Plant Density: Relationships Among Canopy Photosynthesis, Leaf Area and Light Interception. *Crop Science* 31(3): 755-761.

White, H. 1980. A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica* 48(4): 817-838.

Wooldridge, J.M. 2009. *Introductory Econometrics: A Modern Approach.* Mason: South-Western.

## Appendix

## Appendix

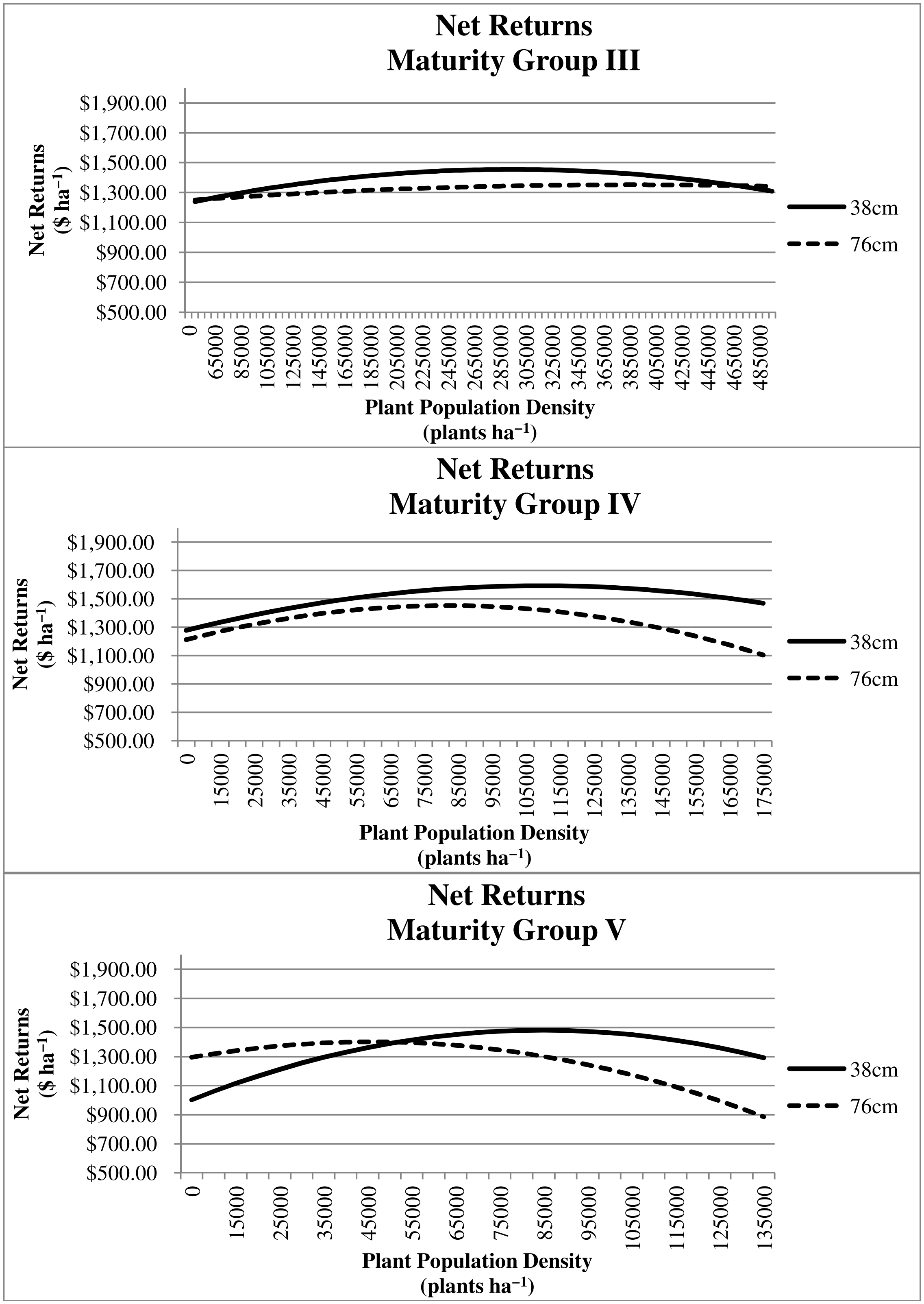


**Figure 2.1.** Net Returns Evaluated at Economically Optimal Plant Population Density Plotted Across Observed Plant Populations by Maturity Group and Row Spacing.

**Table 2.1.** Planting Dates, Cultivars, Row Spacing, Seeding Rates, and Harvest Dates for Experiments by Year and Maturity Group.

| Year | Maturity Group | Planting Date | Cultivar | Row Spacings | Seeding Rates[a] | Harvest Date |
|---|---|---|---|---|---|---|
| 2005 | III | May 10 | Asgrow 3906 Delkab 36-52 | 76 and 38 cm | 346, 395, 445, 494, 519, and 593 | October 7 |
| | IV | May 10 | Pioneer 94B73 Vigoro 42N3 | 76 and 38 cm | 100, 120, 140, 160, and 180 | October 7 |
| | V | May 11 | Vigoro 52N3 | 76 and 38 cm | 80, 100, 120, 140, and 160 | October 12 |
| 2006 | III | May 16 | Asgrow 3906 Pioneer 93M90 | 76 and 38 cm | 247, 296, 371, 445, 519, and 593 | September 27 |
| | IV | May 16 | Pioneer 94B73 Vigoro 42N3 | 76 and 38 cm | 60, 80, 100, 120, 150, and 180 | September 27 |
| | V | May 17 | Vigoro 52N3 | 76 and 38 cm | 60, 80, 100, 120, 150, and 180 | October 24 |
| 2007 | III | May 16 | Asgrow 3906 Pioneer 93M90 | 76 and 38 cm | 247, 296, 371, 445, 519, and 593 | October 2 |
| | IV | May 16 | Pioneer 94B73 Vigoro 42N3 | 76 and 38 cm | 60, 80, 100, 120, 150, and 180 | October 2 |
| | V | May 17 | Vigoro 52N3 | 76 and 38 cm | 60, 80, 100, 120, 150, and 180 | October 3 |

[a]Seeding Rates are $\times 10^3$.

**Table 2.2.** Estimated Regression Coefficients by Maturity Group, Row Spacing, and Year.

| Maturity Group | Row Spacing | Dependent Variable is $Y$[a] $\beta_0$[bc] | $\beta_1$[d] | $\beta_2$[e] | Model F-Statistic | R-squared |
|---|---|---|---|---|---|---|
| | | | | 2005 | | |
| III | 38cm | 4204.57*** | 99.48 | −2.25 | 6.27*** | 0.0969 |
| | 76cm | 6237.03*** | −144.58*** | 3.23*** | 2.91* | 0.1461 |
| IV | 38cm | 4494.65* | 137.93 | −10.67 | 1.02 | 0.0525 |
| | 76cm | 2567.25*** | 350.11 | −16.71 | 1.19 | 0.0605 |
| V | 38cm | 2615.71 | 599.06 | −30.27 | 0.63 | 0.0694 |
| | 76cm | 4535.61*** | 137.15 | −14.42 | 3.87** | 0.3131 |
| | | | | 2006 | | |
| III | 38cm | 3425.13*** | 99.48 | −2.25 | 1.77 | 0.2386 |
| | 76cm | 3210.50*** | 57.08 | −0.63 | 3.42** | 0.1344 |
| IV | 38cm | 3313.35*** | 251.12*** | −9.52*** | 24.83*** | 0.5302 |
| | 76cm | 3483.41*** | 220.64** | −12.50* | 4.47** | 0.1659 |
| V | 38cm | 2549.36*** | 353.48** | −18.63* | 1.19 | 0.1541 |
| | 76cm | 3470.89*** | 194.84 | −18.84 | 1.08 | 0.0932 |
| | | | | 2007 | | |
| III | 38cm | 981.54*** | 76.10*** | −1.38** | 6.01*** | 0.2184 |
| | 76cm | 1502.20*** | 53.17 | −1.57 | 0.95 | 0.0404 |
| IV | 38cm | 2040.53*** | −53.11 | 2.77 | 0.39 | 0.0218 |
| | 76cm | 1780.93*** | −26.93 | 1.61 | 0.07 | 0.0032 |
| V | 38cm | 1275.05*** | 281.88** | −19.49*** | 3.82** | 0.2667 |
| | 76cm | 1655.26*** | 201.75 | −13.88 | 1.20 | 0.1027 |

[a] $Y$ is soybean oilseed yield (kg ha$^{-1}$).
[b] $\beta_0$ is the intercept.
[c] Significance at the 1%, 5%, and 10% levels are denoted by ***, **, and * respectively.
[d] $\beta_1$ is the coefficient on the linear term PPD (10,000 plants ha$^{-1}$).
[e] $\beta_2$ is the coefficient on the squared term PPD$^2$ (10,000 plants ha$^{-1}$).

**Table 2.3.** Weather Conditions: Temperature, Precipitation, and Ångström Index by Year and Month Collected at the Milan Experiment Station in Milan, TN.

| Year | Month | Temperature (°C) | Precipitation (mm) | Ångström |
|---|---|---|---|---|
| 2005 | May | 18 | 15 | 4 |
| | June | 24 | 129 | 26 |
| | July | 26 | 135 | 23 |
| | August | 27 | 205 | 34 |
| | September | 23 | 96 | 21 |
| 2006 | May | 20 | 128 | 33 |
| | June | 24 | 151 | 30 |
| | July | 27 | 90 | 15 |
| | August | 27 | 84 | 14 |
| | September | 20 | 114 | 30 |
| 2007 | May | 22 | 58 | 13 |
| | June | 25 | 112 | 21 |
| | July | 25 | 55 | 10 |
| | August | 30 | 32 | 4 |
| | September | 23 | 184 | 39 |
| 100 Year Average | May | 20 | 129 | 34 |
| | June | 24 | 104 | 21 |
| | July | 26 | 108 | 19 |
| | August | 26 | 94 | 17 |
| | September | 22 | 93 | 21 |

**Table 2.4.** Weighted Average Response Coefficients by Maturity Group and Row Spacing.

| Maturity Group | Row Spacing | Dependent Variable is $Y$[ab] | | |
|---|---|---|---|---|
| | | $\beta_0$[cd] | $\beta_1$[e] | $\beta_2$[f] |
| III | 38cm | 3160.63*** | 67.94** | −0.97* |
| | 76cm | 3369.71*** | 28.52 | −0.24 |
| IV | 38cm | 3283.09*** | 189.04** | −7.81** |
| | 76cm | 3096.79*** | 200.85** | −10.94** |
| V | 38cm | 2364.26*** | 376.62*** | −20.37*** |
| | 76cm | 3341.70*** | 187.89 | −17.47 |

[a]$Y$ is soybean oilseed yield (kg ha$^{-1}$).
[b]Weights: 2005 = 0.1387, 2006 = 0.7089, and 2007 = 0.1525.
[c]$\beta_0$ is the intercept.
[d]Significance at the 1%, 5%, and 10% levels are denoted by ***, **, and * respectively.
[e]$\beta_1$is the coefficient on the linear term PPD (10,000 plants ha$^{-1}$).
[f]$\beta_2$ is the coefficient on the squared term PPD$^2$ (10,000 plants ha$^{-1}$).

**Table 2.5.** Biologically and Economically Optimal Plant Population Densities, Yields, and Net Returns for the Year 2005 by Maturity Group and Row Spacing.

| Maturity Group | Row Spacing | BOPPD[a] | EOPPD[b] | Wald Statistic[cd] | Net Returns[e] |
|---|---|---|---|---|---|
| III | 38 cm | 221,140<br>(5,304)[f] | 198,406<br>(5,293) | 1.15 | $1,846.00 |
| | 76 cm | 348,602<br>(5,123) | 348,602<br>(5,123) | N/A[g] | $1,731.74 |
| IV | 38 cm | 64,650<br>(4,941) | 59,857<br>(4,938) | 0.20 | $1,767.20 |
| | 76 cm | 104,735<br>(4,401) | 101,675<br>(4,399) | 2.13 | $1,557.45 |
| V | 38 cm | 98,958<br>(5,580) | 97,269<br>(5,579) | 1.93 | $1,990.04 |
| | 76 cm | 47,571<br>(4,862) | 44,023<br>(4,860) | 2.47 | $1,749.68 |

[a]Biologically optimal plant population density (BOPPD) in plants $ha^{-1}$.
[b]Economically optimal plant population density (EOPPD) in plants $ha^{-1}$.
[c]Wald test for $BOPPD_{j,k}=EOPPD_{j,k}$ (d.f.=1, $\alpha$=.10, critical $\chi^2$ value=2.71).
[d]Significance at the 1%, 5%, and 10% levels are denoted by ***, **, and * respectively.
[e]Net Returns ($ $ha^{-1}$) were calculated at the EOPPD using equation (8).
[f]Yields (kg $ha^{-1}$) evaluated at BOPPD and EOPPD are in parentheses.
[g]Due to the convex shape of the original response curve this MG, RS combination was evaluated as a corner solution, therefore BOPPD and EOPPD were not tested.

**Table 2.6.** Biologically and Economically Optimal Plant Population Densities, Yields, and Net Returns for the Year 2006 by Maturity Group and Row Spacing.

| Maturity Group | Row Spacing | BOPPD[a] | EOPPD[b] | Wald Statistic[cd] | Net Returns[e] |
|---|---|---|---|---|---|
| III | 38 cm | 470,563 (4,837)[f] | 390,378 (4,796) | 1.02 | \$1,589.75 |
| | 76 cm | 450,971 (4,498) | 370,174 (4,456) | 0.35 | \$1,477.04 |
| IV | 38 cm | 131,833 (4,969) | 126,464 (4,966) | 41.41*** | \$1,752.31 |
| | 76 cm | 88,225 (4,457) | 84,136 (4,454) | 3.47* | \$1,584.60 |
| V | 38 cm | 94,882 (4,226) | 92,137 (4,225) | 3.80* | \$1,491.29 |
| | 76 cm | 51,708 (3,975) | 48,994 (3,973) | 1.28 | \$1,419.89 |

[a]Biologically optimal plant population density (BOPPD) in plants $ha^{-1}$.
[b]Economically optimal plant population density (EOPPD) in plants $ha^{-1}$.
[c]Wald test for $BOPPD_{j,k}=EOPPD_{j,k}$ (d.f.=1, $\alpha$=.10, critical $\chi^2$ value=2.71).
[d]Significance at the 1%, 5%, and 10% levels are denoted by ***, **, and * respectively.
[e]Net Returns (\$ $ha^{-1}$) were calculated at the EOPPD using equation (8).
[f]Yields (kg $ha^{-1}$) evaluated at BOPPD and EOPPD are in parentheses.

**Table 2.7.** Biologically and Economically Optimal Plant Population Densities, Yields, and Net Returns for the Year 2007 by Maturity Group and Row Spacing.

| Maturity Group | Row Spacing | BOPPD[a] | EOPPD[b] | Wald Statistic[cd] | Net Returns[e] |
|---|---|---|---|---|---|
| III | 38 cm | 275,822 (2,031)[f] | 238,775 (2,012) | 6.54** | \$617.60 |
| | 76 cm | 169,028 (1,952) | 136,521 (1,935) | 2.25 | \$633.10 |
| IV | 38 cm | 178,886 (1,977) | 178,886 (1,977) | N/A[g] | \$627.25 |
| | 76 cm | 13,358 (1,748) | 13,358 (1,748) | N/A[g] | \$610.47 |
| V | 38 cm | 72,321 (2,294) | 69,697 (2,293) | 7.68*** | \$785.41 |
| | 76 cm | 72,667 (2,388) | 68,984 (2,386) | 0.12 | \$825.56 |

[a]Biologically optimal plant population density (BOPPD) in plants $ha^{-1}$.
[b]Economically optimal plant population density (EOPPD) in plants $ha^{-1}$.
[c]Wald test for $BOPPD_{j,k}$=$EOPPD_{j,k}$ (d.f.=1, α=.10, critical $\chi^2$ value=2.71).
[d]Significance at the 1%, 5%, and 10% levels are denoted by ***, **, and * respectively.
[e]Net Returns (\$ $ha^{-1}$) were calculated at the EOPPD using equation (8).
[f]Yields (kg $ha^{-1}$) evaluated at BOPPD and EOPPD are in parentheses.
[g]Due to the convex shape of the original response curve this MG, RS combination was evaluated as a corner solution, therefore BOPPD and EOPPD were not tested.

**Table 2.8.** Biologically and Economically Optimal Plant Population Densities, Yields, and Net Returns by Maturity Group and Row Spacing.

| Maturity Group | Row Spacing | BOPPD[a] | EOPPD[b] | Wald Statistic[cd] | Net Returns[e] |
|---|---|---|---|---|---|
| III | 38 cm | 348,673 (4,345)[f] | 296,118 (4,318) | 3.24*** | $1,448.63 |
| | 76 cm | 507,840[g] (4,216) | 380,442 (4,107) | N/A[g] | $1,343.93 |
| IV | 38 cm | 121,051 (4,427) | 114,503 (4,424) | 4.98** | $1,556.42 |
| | 76 cm | 91,824 (4,019) | 87,148 (4,017) | 4.58** | $1,421.47 |
| V | 38 cm | 92,431 (4,105) | 89,921 (4,104) | 7.37*** | $1,447.25 |
| | 76 cm | 53,774 (3,847) | 50,847 (3,845) | 1.70 | $1,371.91 |

[a]Biologically optimal plant population density (BOPPD) in plants $ha^{-1}$.
[b]Economically optimal plant population density (EOPPD) in plants $ha^{-1}$.
[c]Wald test for $BOPPD_{j,k}=EOPPD_{j,k}$ (d.f.=1, α=.10, critical $\chi^2$ value=2.71).
[d]Significance at the 1%, 5%, and 10% levels are denoted by ***, **, and * respectively.
[e]Net Returns ($ $ha^{-1}$) were calculated at the EOPPD using equation (8).
[f]Yields (kg $ha^{-1}$) evaluated at BOPPD and EOPPD are in parentheses.
[g]Estimated BOPPD was beyond the observed PPD, therefore this is the highest observed PPD and was not tested.

**Table 2.9.** Comparisons of Net Returns among Maturity Group, Row Spacing Combinations.

| | | Maturity Group, Row Spacing Combinations[a] | | | | | |
|---|---|---|---|---|---|---|---|
| | | MG III, 38cm[b] | MG III, 76cm | MG IV, 38cm | MG IV, 76cm | MG V, 38cm | MG V, 76cm |
| Maturity Group, Row Spacing Combinations | MG III, 38cm | — | | | | | |
| | MG III, 76cm | 6.54** | — | | | | |
| | MG IV, 38cm | 12.87*** | 28.03*** | — | | | |
| | MG IV, 76cm | 0.88 | 3.89** | 23.62*** | — | | |
| | MG V, 38cm | 0.00 | 4.71** | 7.98*** | 0.47 | — | |
| | MG V, 76cm | 5.56** | 0.44 | 34.23*** | 2.65 | 3.44* | — |

[a]Values are Wald statistics from tests for differences in net returns (\$ $ha^{-1}$), $NR_{j,k}$=$NR_{j,k}$ (d.f.=1, $\alpha$=.10, critical $\chi^2$ value=2.71).
[b]Significance at the 1%, 5%, and 10% levels are denoted by ***, **, and * respectively.

# Chapter 3: The Adoption of Information Technologies and Subsequent Changes in Input Use in Cotton Production

**Abstract**

Precision agriculture technology has become increasingly important in crop production. It allows farmers to take advantage of knowledge about in-field variability by using variable rate technology (VRT) to apply inputs at levels appropriate to current soil or crop needs. This affords farmers the potential for increased profit realized via increased yields, reduced input use, or both. Applying inputs using VRT may also limit potentially damaging environmental impacts such as groundwater contamination from the leaching of over applied inputs. Both the economic and environmental benefits of precision agriculture can be traced back to increased productivity of input use. The factors affecting this increased productivity following VRT management have been evaluated in previous literature. However, the factors affecting specific directional changes (increase, no change, or decrease) of overall input use following VRT have not been evaluated. Hence, the objective of this study was to evaluate the factors influencing the decision by cotton growers to adopt one or more information technologies for VRT application of inputs, and farmer perceptions of directional changes in input use. Data about cotton farmer adoption of alternative information technologies for VRT application of inputs were from the 12-state 2009 Southern Cotton Precision Farming Survey. Given the sequential nature of adoption and perceptions of changes in input use, models were initially estimated using a Heckman Probit model to account for potential sample selection bias. The explanatory variables included in the model were: characteristics describing the farm operation and farm decision maker, sources of precision agriculture information used by the farm decision maker, and regional dummy variables for farm location. Results from the initial estimation failed to reject the hypothesis that correlation between the error terms of the selection and outcome equations was equal to zero, meaning the models were not significantly affected by sample selection bias and could be

evaluated as individual binomial Probit models. Results suggest that cotton farmers in the sample who used picker rather than stripper harvest technology were more likely to perceive that overall fertilizer use declined with the use of the selected information technologies and VRT. This result and other key findings of this research may not only be of interest to other cotton farmers but also to the USDA Natural Resource Conservation Service, who may be interested in the environmental impacts of decreased fertilizer use among cotton farmers, and University Extension, who are involved in educating farmers about precision agriculture. Finally, the results of this research lay the groundwork for future research to build upon regarding directional changes in fertilizer use, as well as the use of other inputs.

## Introduction

Prior to the advent of precision farming, farmers typically applied inputs using uniform rate technology (URT). Depending on the amount of in-field variability, URT commonly leads to under or over utilization of inputs in more productive and less productive sections of farm fields, respectively. Precision farming involves “collecting site-specific information about within-field variability in yields and crop needs, linking that information to specific locations within a field, and acting on that information to determine and apply appropriate input levels” (Mooney et al. 2010, p.6). Thus, precision farming allows farmers to take advantage of knowledge of in-field variability, leading to increased input productivity (Roberts et al. 2004). However, directional changes in overall input use vary by site and circumstance (Batte 2000; Lambert, Lowenberg-DeBoer, and Malzer 2006). The ability to understand the factors affecting farmer perceptions of changes in overall input use following VRT management is important because precision farming technologies have the potential to increase profit and reduce potential negative environmental effects of inefficient input management.

Research has shown that precision farming affords the potential for economic benefits (Lambert and Lowenberg-DeBoer 2000; Swinton and Lowenberg-DeBoer 1998). This is especially true for cotton given it is a high-value crop that requires the extensive use of chemicals and fertilizers (Brooks 2001; Griffin et al. 2004; Larson et al. 2008). The ability to apply inputs according to current crop and/or soil needs using VRT input management commonly leads to increased input efficiency (Roberts et al. 2004). As a result, farmers have the potential for increased profit realized via yield increases, reduced input use, or both, when compared to URT (Babcock and Pautsch 1998; English, Mahajanashetti, and Roberts 2001; Roberts, English, and Mahajanashetti 2000).

Precision farming also has the potential to reduce negative environmental impacts such as surface and groundwater contamination from runoff and leaching that result from the over application of inputs (Roberts et al. 2002; Wang et al. 2003; Watkins, Lu, and Huang 1998). Although these environmental benefits can be difficult to quantify, they are based on the implicit assumption that improved input efficiency, realized through precision farming, translates to improved environmental quality (Larkin et al. 2005). Larkin et al. (2005) found that total planted area, higher yields, computer use, perceived profitability of precision farming, and perceived importance of reducing input use all positively influenced farmer perceptions about the importance of precision farming in improving environmental quality.

Currently available literature concerning precision farming's effect on changes in input use focus on improvements in input efficiency (Khanna 2001; Torbett et al. 2007, 2008). Khanna (2001) evaluated determinates of nitrogen productivity (yield per unit of nitrogen) following the adoption of site-specific soil test and VRT management among grain farmers in the Midwest. College education was the only explanatory variable that significantly influenced increased nitrogen productivity, suggesting that other unobserved factors such as soil quality may be important in explaining differences in input productivity among farmers (Khanna 2001). Torbett et al. (2007, 2008) evaluated the factors affecting farmer perceptions of the importance of precision farming technologies in improving the efficiency of phosphorus (P), potassium (K), and nitrogen (N) in cotton production. Using an ordered logit model, they found the use of yield monitor without GPS, management zone soil sampling, grid soil sampling, and on-the-go sensing to be important in increasing P, K, and N efficiency (Torbett et al. 2007, 2008). Also, positive perceptions of the importance of precision farming technologies were found to be more likely among older farmers who used computers for farm management and rented larger portions of the land they farmed (Torbett et al. 2007, 2008). While understanding the factors influencing improved input productivity have been beneficial to understanding the potential benefits of precision farming, there is a need to further understand improvements in input productivity. Hence, understanding the factors influencing farmer perceptions of specific directional changes in overall input use (increase, no change or decrease) may be beneficial to understanding the benefits of precision farming.

Prior to perceiving changes in input use, a farmer must first make the decision to adopt. This decision is based on the expected utility a farmer derives from the adoption and use of precision farming technologies; where utility refers to the overall level of satisfaction that may be a influenced by both economic and environmental benefits (Torbett et al. 2008). The adoption of precision farming has been extensively evaluated in prior research (Batte and Arnholt 2003; Daberkow and McBride 1998; Griffin et al. 2004; Khanna 2001; Kotsiri et al. 2011; Lambert et al. 2007; Larson et al. 2008; Marra et al. 2010; Popp and Griffin 2000; Roberts et al. 2004; Surjandari and Batte 2003; Walton et al. 2008; Walton et al. 2010).

The objective of this research was to determine the characteristics that influence farmer decisions to adopt select information technologies for VRT management of inputs, and the subsequent perceptions of directional changes in overall application of selected inputs. There does not appear to be any literature evaluating the factors affecting farmer perceptions of directional changes in input use following the adoption of one or more information technologies. Knowledge of the factors motivating both adoption and subsequent perceptions of changes in input use may provide further insight into the potential benefits of precision farming realized through increased input productivity.

## Methods and Procedures

### *Analytical Framework*

A farmer is hypothesized to make decisions to maximize expected utility through profit. Therefore, let $U_A$ represent the expected utility of profit from adopting one or more information technologies for VRT application of inputs and $U_{NA}$ represent the expected utility from not adopting any information technologies. Defining $U_A^* = U_A - U_{NA}$, the farmer who maximizes expected utility will choose to adopt when $U_A^* > 0$ and not adopt when $U_A^* < 0$. The unobservable latent variable $U_A^*$ is assumed to be a random function of a vector of observable exogenous variables $Z_A$:

(1) $U_A^* = Z_A \gamma_A + \varepsilon_A$,

where $\gamma_A$ is a vector of unknown parameters and $\varepsilon_A$ is the random error. While $U_A^*$ is not directly observable, a farmer's observable decision to adopt can be represented by the following binary variable (Khanna 2001):

(2) $I_A = 1$ if $U_A^* > 0$,
$= 0$ otherwise.

Farmers who choose to adopt one or more information technologies for VRT application are subsequently self-selected into the group of farmers who are conceivably able to have perceptions regarding directional changes in input use. This sequence suggests the use of econometric methods that account for sample-selection bias (Heckman 1979; Khanna 2001; Roberts et al, 2004; Walton et al. 2008). Thus, the previously defined adoption model is the selection equation, and the outcome equation modeling farmer perceptions of directional changes in input use can be modeled as:

(3) $I_P = Z_P \gamma_P + \varepsilon_P$

where $I_P = 1$ if a farmer perceives a specific directional change in input use given that $I_A = 1$, and zero otherwise; $Z_P$ is a vector of observable exogenous variables hypothesized to affect these perceptions; $\gamma_P$ is a vector of unknown parameters; and $\varepsilon_P$ is the random error term. A farmer who maximizes expected utility will choose to:

(4) adopt one or more information technologies for the VRT application of inputs and perceive a given directional change in input use when $U_A^* > 0$ and $I_P = 1$,

(5) adopt one or more information technologies for the VRT application of inputs and not perceive a given directional change in input use when $U_A^* > 0$ and $I_P = 0$, or

(6) not adopt any information technologies when $U_A^* < 0$.

Assuming the error terms $\varepsilon_A$ from equation (1) and $\varepsilon_P$ from equation (3) are both normally distributed with a mean of zero and variance of one, the choices characterized by equations (4) – (6) can be expressed in terms of the following probabilities:

$$\text{(7)}\ \Pr(I_A = 1 \text{ and } I_P = 1) = \Pr(I_P = 1 \mid I_A = 1) \times \Pr(I_A = 1) = \Phi_2(Z_A\,\gamma_A, Z_P\,\gamma_P, \rho),$$

$$\text{(8)}\ \Pr(I_A = 1 \text{ and } I_P = 0) = \Pr(I_P = 0 \mid I_A = 1) \times \Pr(I_A = 1) = \Phi_2(Z_A\,\gamma_A, -Z_P\,\gamma_P, -\rho),$$

$$\text{(9)}\ \Pr(I_A = 0) = 1 - \Pr(I_A = 1) = \Phi(-Z_A\,\gamma_A),$$

where $\Phi_2$ and $\Phi$ are cumulative distribution functions for the standard bivariate normal and standard normal distributions respectively, and $\rho$ is the correlation between $\varepsilon_A$ and $\varepsilon_P$ (Greene 2003; Miranda and Rabe-Hesketh 2006).

If $\rho$ is not zero, the model can be estimated as a bivariate probit model with sample selection using maximum likelihood. The probabilities in equations (7) – (9) form the sample likelihood function as (Greene 2003; Roberts et al. 2004):

$$\text{(10)}\ \mathrm{L} = \prod_{I_A=1,I_P=1} \Phi_2(Z_A\,\gamma_A, Z_P\,\gamma_P, \rho) \prod_{I_A=1,I_P=0} \Phi_2(Z_A\,\gamma_A, -Z_P\,\gamma_P, -\rho) \prod_{I_P=0} \Phi(-Z_A\,\gamma_A).$$

If $\rho$ is zero, the bivariate distribution reduces to the product of two univariate distributions, and the likelihood function becomes (Greene 2003; Roberts et al. 2004):

$$(11)\ \mathrm{L} = \prod_{I_A=1,I_P=1} \Phi(Z_A\,\gamma_A)\Phi(Z_P\,\gamma_P) \prod_{I_A=1,I_P=0} \Phi(Z_A\,\gamma_A)\Phi(-Z_P\,\gamma_P) \prod_{I_P=0} \Phi(-Z_A\,\gamma_A)$$

$$= \prod_{I_A=1} \Phi(Z_A\,\gamma_A) \prod_{I_A=0} \Phi(-Z_A\,\gamma_A) \prod_{I_A=1,I_P=1} \Phi(Z_P\,\gamma_P) \prod_{I_A=1,I_P=0} \Phi(-Z_P\,\gamma_P).$$

Thus, the model fails to identify sample selection bias and equations (1) and (3) can be estimated as separate binomial probit models (Greene 2003).

***Data***

The data for this study were collected from a 2009 survey of cotton producers in 12 southern states: Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, Texas, and Virginia. The Cotton Board in Memphis, Tennessee, provided a list of 14,089 potential cotton producers from their 2007-2008 marketing year lists. Following the general mail survey procedures of Dillman (1978), a questionnaire, postage-paid return envelope, and a cover letter outlining the importance of the survey were sent to each producer. The initial mailing was on February 20, 2009. A reminder post card was sent two weeks later on March 5, 2009. For those not responding, a follow-up mailing containing a questionnaire, postage paid return envelope, and a letter reemphasizing the importance of the survey was sent March 27, 2009. Of the surveys initially mailed, 306 were returned as undeliverable and 204 indicated they had either retired or did not farm cotton. Assuming all remaining non-respondents and the 85 who declined participation are active cotton producers, the total number of cotton producers surveyed was 13,579. Of the responses received, 1,692 were counted as valid. Calculating the survey response rate as the number of valid responses divided by the number of cotton farmers surveyed, the response rate was 12.5% (Mooney et al. 2010). Also included in this analysis were secondary data representing the number of farm input suppliers at the county level. These data were collected from the U.S. Census Bureau 2007 County Business Patterns (CBP) (U.S. Census Bureau 2011). The number of establishments was extracted using North American Industry Classification System (NAICS) codes 423820 and 424910 for "Farm and Garden Machinery and Equipment Merchant Wholesalers" and "Farm Supplier Merchant Wholesalers" respectively (U.S. Census Bureau 2011).

The survey was developed to collect information concerning cotton producers' use and perceptions of precision farming technologies, including site-specific information and VRT. This study is based on questions 17 and 18 from the survey (Figure 3.1). Question 17 asked farmers to indicate the specific information technologies (i.e. yield monitors, passive remote sensing, PDA/handheld GPS, electrical conductivity, and GreenSeeker) that were used to make selected VRT decisions (i.e. drainage, fertility or lime, seeding, growth regulator, harvest aids, fungicide, herbicide, insecticide, and irrigation). To avoid confusion, it is acknowledged that the adoption of information technologies does not automatically indicate VRT application of inputs. But given the wording of question 17 it is assumed for this model that farmers adopting information technologies are using them for VRT decisions. Question 18, which is a follow up to question 17 asked farmers about their perceptions of changes in the overall use of select inputs (i.e. fertilizer, lime, seed, growth regulator, harvest aids, fungicide, herbicide, insecticide, and irrigation) as a result of VRT management. Given the initial overrepresentation of larger farmers, post-stratification survey weights estimated by Harper et al. (2011) were used to align survey data with the 2007 United States Department of Agriculture (USDA) Agricultural Census by state and farm size class. Post-stratification weights can adjust for over or underrepresentation of survey within strata (e.g. state or farm size class), but do not correct for potential non-response bias (Lohr 1999).

***Comparison of Sample Means***

Farm business and farmer characteristics were compared between different subsets of the population for adopters and non-adopters as well as for the subsets of various perceptions of directional changes in overall input use. By comparing these subsets of the sample, further insight can be drawn as to the factors affecting farmer decisions to adopt technologies and their perceptions about changes in input use. To stay consistent with the regression analysis, means were estimated using post-stratification survey weights. Differences among means were tested using side-by-side *t*-tests.

***Empirical Models***

The model for the adoption of one or more selected information technologies for the VRT application of inputs as a function of farmer and farm business characteristics was specified as follows:

$$(12)\ ADOPT_i = \beta_1 AGE_i + \beta_2 EDUC_i + \beta_3 INC_i + \beta_4 INCFRM_i + \beta_5 COMP_i + \beta_6 LIVSTK_i + \beta_7 COTAREA_i + \beta_8 OWNRENT_i + \beta_9 IRRIG_i + \beta_{10} PICKER_i + \beta_{11} FRMSPLY_i + \beta_{12} FRMDLER_i + \beta_{13} CRPCSLT_i + \beta_{14} OFRMER_i + \beta_{15} EXTEN_i + \beta_{16} TRDSHW_i + \beta_{17} INTER_i + \beta_{18} MEDIA_i + \beta_{19} NOINFO_i + \beta_{20} ERS1_i + \beta_{21} ERS4_i + \beta_{22} ERS5_i + \beta_{23} ERS6_i + \beta_{24} ERS7_i + \beta_{25} ERS9_i + e_i$$

where *ADOPT* equals one if producer *i* adopted one or more of the following information technologies, yield monitor, passive remote sensing, PDA/handheld GPS device, active remote sensing, or electrical conductivity, for VRT management of inputs and zero otherwise. $\beta_1$ through $\beta_{25}$ are parameters to be estimated and *e* is the random error term. Variable names, definitions, hypothesized signs, and means for independent variables are found in Table 3.1.

Subsequently, farmers who choose to adopt one or more of the select information technologies are self-selected into the group of farmers who are conceivably able to perceive directional changes in the use of select inputs. This model was applied to several inputs, but due to missing observations for some inputs, only the model evaluating perceptions of changes in fertilizer use was evaluated. Models for farmer perceptions of directional changes in fertilizer use, as a function of farmer and farm characteristics, were specified as follows:

$$(13)\ FERTILIZER_j = \theta_1 AGE_j + \theta_2 EDUC_j + \theta_3 INC_j + \theta_4 INCFRM_j + \theta_5 COMP_j + \theta_6 COTAREAj + \theta_7 OWNRENT_j + \theta_8 IRRIG_j + \theta_9 PICKER_j + \theta_{10} FRMSPLY_j + \theta_{11} FRMDLER_j + \theta_{12} CRPCSLT_j + \theta_{13} OFRMER_j + \theta_{14} EXTEN_j + \theta_{15} TRDESHW_j + \theta_{16} INTER_j + \theta_{17} MEDIA_j + e_j$$

where *FERTILIZER* equals one if producer *j* perceived the change of interest in fertilizer use and zero otherwise, $\theta_1$ through $\theta_{17}$ are parameters, and *e* is the random error term. Given the construction of the survey, farmers were able to indicate one of three perceived changes in the use of each input: increase, no change, or decrease. To evaluate the factors affecting each of these perceptions, the model was estimated three times, redefining the binary outcome variable of equation (14). Dependant variables in the three models were defined as:

$$(14)\quad FERTILIZER_{j,1} = 1 \text{ if input use increased}$$
$$= 0 \text{ otherwise (input use did not change or decreased)}$$
$$(15)\quad FERTILIZER_{j,2} = 1 \text{ if input use did not change}$$
$$= 0 \text{ otherwise (input use increased or decreased)}$$
$$(16)\quad FERTILIZER_{j,3} = 1 \text{ if input use decreased}$$
$$= 0 \text{ otherwise (input use increased or did not change).}$$

Names, definitions, hypothesized signs, and means for independent variables can also be found in Table 3.1.

Also note that both equations (13) and (14) were restricted to no intercept term and all dummy variables were included to aid in model estimation (Butler 1996).

***Hypotheses***

Variables explaining adoption include proxies for farmer and farm characteristics, sources of precision farming information, and farm location. Hypotheses for these variables were based on a review of precision farming adoption literature (Batte, Jones, and Schnitkey 1990; Daberkow and McBride 1998; Khanna 2001; Kotsiri et al. 2011; Larson et al. 2008; Roberts et al. 2004; Surjandari and Batte 2003; Walton et al. 2008; Walton et al. 2010). Farmer perceptions of directional changes in overall fertilizer use are expected to be influenced by the endogenous adoption decision as well as exogenous farmer and farm operation characteristics and sources of precision farming information. Hypotheses for these variables were based on a review of literature associated with the effects of precision farming on input use (Khanna 2001; Roberts, English, and Larson 2006; Roberts, English, and Mahajanashetti 2000; Torbett et al. 2007, 2008). The variable representing livestock ownership (LIVSTK) was excluded as an explanatory variable because, while it is expected to affect the adoption of information technologies, it is not expected to have a direct impact on perceptions of directional changes in fertilizer use. The proxy for failure to use any information sources (NOINFO) was excluded because the sub-sample of adopters showed little to no variation. Regional dummy variables were also excluded because the sub-sample of adopters contained too few observations for some of the regions.

Five farmer characteristics were hypothesized to affect the decision to adopt one or more information technologies for VRT application of inputs and the subsequent perception of directional changes in fertilizer use. The age of the primary decision maker (AGE) was hypothesized to be negatively associated with adoption and the perception that fertilizer use did not change. Younger farmers were expected to have a longer time horizon to realize the benefits of adoption, whereas older farmers were hypothesized to be less interested in investing in new technologies (Batte, Jones, and Schnitkey 1990; Roberts et al. 2004; Walton et al. 2008). An older farmer was also expected to have the experience needed to better recognize changes in fertilizer use in one direction or the other, making them less likely to perceive no change in fertilizer use (Torbett et al. 2008).

Farmers who held a Bachelor's degree or higher (EDUC) were hypothesized to be more likely to adopt and to perceive fertilizer use to increase or decrease. A college education was expected to equip a farmer with the higher level of analytical ability needed to deal with the volume and intricacy of data associated with precision farming (Batte, Jones, and Schnitkey 1990; Roberts et al. 2004; Walton et al. 2008). Much in the same way, a farmer with a college degree was expected to have the level of analytical ability needed to recognize changes in fertilizer use no matter how small in either direction (Torbett et al. 2007, 2008).

Household income over $100,000 (INC) was hypothesized to be positively associated with adoption. This threshold was selected based on the approximate median household income of cotton farmers (USDA – ERS 2011). Higher income was expected to potentially facilitate initial investment into precision farming technologies (Daberkow and McBride 1998; Walton et al. 2008). The effect of INC on farmer perceptions of directional changes in fertilizer use was unable to be hypothesized *a priori*. Higher income could facilitate the ability to invest in complementary technologies that would help to realize reductions in fertilizer use, but it could also provide a farmer with the financial ability to invest in higher levels of fertilizer application if that is what collected information indicates is needed (Walton et al. 2008).

The percentage of household income from farming operations (INCFRM) was hypothesized to positively influence adoption and the perception that fertilizer use increased or decreased. A farmer who earned a larger portion of their income from farming was assumed to spend more time attending to those operations, and therefore was expected to have a higher probability of adopting time and management intensive technologies (Cooper and Keim 1996;

Khanna 2001). In much the same way, farmers earning a larger portion of their income from farming were expected to have more time to learn and realize the full potential of the technologies, potentially increasing fertilizer productivity (D'Souza, Cyphers, and Phipps 1983; Khanna 2001).

The use of a computer to manage the farm operation (COMP) was hypothesized to positively influence adoption and negatively influence the perception that fertilizer use did not change. Because computer technology is integrated into precision farming, a farmer with previous experience using a computer was more likely to adopt (Walton et al 2008). Familiarity with computers may also facilitate more efficient manipulation and use of collected data increasing fertilizer productivity (Torbett et al. 2007, 2008).

Six farm characteristics were expected to affect the adoption decision, five of which were expected to affect the perception of directional changes in fertilizer use. Ownership of livestock (LIVSTK) was hypothesized to negatively affect adoption (Surjandari and Batte, 2003; Walton et al., 2010). Time spent managing an enterprise not directly related to cotton production was hypothesized to reduce the time available for managing crops. While this variable was expected be associated with the adoption of information technologies, it was not expected to influence farmer perceptions of directional changes in fertilizer use.

Cotton area planted (COTAREA) was hypothesized to be positively associated with adoption and perceptions of an increase or a decrease in fertilizer use. When the fixed cost of information technologies can be spread over a larger area of cotton, a farmer would be expected to invest in precision agricultural technologies (Roberts et al. 2004; Walton et al. 2010). A farm with a larger area of cotton was expected to be subject to larger spatial variability, and therefore may be more likely to increase in fertilizer productivity following VRT application of inputs (Roberts et al. 2004; Torbett et al. 2007; Walton et al. 2010).

The percentage of total cotton area owned (OWNRENT) was hypothesized to be positively associated with adoption and negatively affect the perception of an increase or a decrease in fertilizer use. Information technologies and the spatially referenced data they are used to collect are potentially useful for several growing seasons, and land ownership may help to ensure return of this investment because of the ability to pass owned land on to subsequent generations while rental contracts can vary in length (Daberkow and McBride 1998; Walton et al. 2008). A farmer owning a larger portion of their land may also be more likely to already know more about the variability of their fields and not recognize significant changes in fertilizer use as a result of VRT (Torbett et al. 2007).

The presence of irrigation on a farm (IRRIG) was hypothesized to positively influence the adoption decision and the perception that fertilizer use increased. Irrigated cotton is generally associated with higher yields and the need for potentially higher input levels (Baerenklau and Knapp 2007; Monks et al. 2007). Therefore, there may be more opportunities for the use information technologies to vary inputs in different parts of irrigated fields (Larson et al. 2008). Also, the recognized interaction between irrigation and fertilizer was expected to make the perception that fertilizer use increased more likely among those who used irrigation (Larson et al. 2008; Roberts, English, and Larson 2006).

A dummy variable representing the use of a cotton picker (PICKER) was included in both the adoption and the perceived changes in fertilizer use equations as a technological proxy for a variety of factors including production techniques and location (Boman et al. 2011). Picker cotton is typically considered the higher value alternative to stripper cotton which is often subject to discounts for higher leaf and bark content in the lint (Larson et al. 2004; Valco, Anthony, and McAlister 2001). Also, picker cotton and stripper cotton are region specific, with stripper cotton being grown predominantly in the high plains of Texas and Oklahoma and picker cotton largely everywhere else (Boman et al. 2011). PICKER was hypothesized to positively affect adoption. A farmer growing picker cotton was expected to be more likely to adopt information technologies due to its higher expected value. PICKER was also anticipated to contribute to the perception of an increase or a decrease in fertilizer use based on the physiology of cotton growth. Farmers growing picker cotton were expected to be less likely to perceive an increase and more likely to perceive a decrease in fertilizer use because the over application of fertilizer, especially nitrogen, can shift the growth of cotton plants away from reproductive growth of cotton bolls and towards more vegetative growth, leading to discounts for leaf and bark content in the lint (Gaylor et al. 1983; Howard et al. 2001; Kohli and Morrill 1976). Plant growth regulators and harvest aids can also be used to compensate for over application of nitrogen, but can be expensive and are therefore only used as needed (Fritschi et al. 2003).

The number of farm input suppliers within the county (FRMSPLY) was hypothesized to positively affect adoption. It was expected that closer proximity to more local farm input suppliers would increase a farmer's knowledge of information technologies (Khanna 2001). The effect of FRMSPLY on the perception of changes in fertilizer was difficult to predict *a priori*.

Dummy variables representing farmer sources of information concerning precision farming technologies were also included in both models. Each of the seven sources were included as a dummy variable equal to one if a farmer indicated receiving information from that source and zero otherwise. The sources include farm dealers (FRMDLER), crop consultants (CRPCSLT), University Extension (EXTEN), other farmers (OFRMER), trade shows

(TRDESHW), the internet (INTER), and news or media outlets (MEDIA). Also included in the adoption model was a dummy variable representing farmers who did not use any of the information sources or did not answer the question (NOINFO). NOINFO was hypothesized to negatively influence the adoption of information technologies due to the expected general lack of knowledge about the technologies. The effects of the remaining information sources on adoption and directional changes in fertilizer use are unknown *a priori*.

Dummy variables representing the regions where a farm was located were included in the adoption model. USDA Economic Research Service (USDA – ERS) Farm Resource Regions were used because of the factors they were created to capture such as farm production characteristics, soil characteristics, and climatic traits (USDA – ERS 2012). The Heartland (ERS1), Prairie Gateway (ERS4), Eastern Uplands (ERS5), Southern Seaboard (ERS6), Fruitful Rim (ERS7), and Mississippi Portal (ERS9) were all included in the model, equal to one if the respondent's operation is located in that region and zero otherwise. Limited availability of previous literature evaluating regional characteristics affect on adoption decisions made it difficult to make hypotheses for these variables *a priori*.

***Statistical Analysis***

Equations (12) and (13) were tested for multicollinearity among independent variables using the COLLIN statement in STATA 12.0 (StataCorp 2011). Multicollinearity occurs when two or more independent variables are highly correlated with each other. If present, multicollinearity causes standard errors to be inflated, which in turn can affect the significance and inferential power of coefficients (Chatterjee and Price 1991). Variance inflation factors (VIF) were used to detect collinear variables. Typically, VIFs greater than 10 are thought to indicate the presence inflated standard errors.

Equations (12) and (13) were first estimated simultaneously using maximum likelihood for each of the three directional changes in fertilizer use using the HECKPROB command in STATA 12.0 (StataCorp 2011). Models were weighted using the PWEIGHT option, including the post-stratification weights (StataCorp 2011). A Wald test was used to test the null hypothesis that the cross-equation correlation coefficient $\rho$ was equal to zero. Rejection of this hypothesis indicates correlation between the error terms and the need to estimate the models using the bivariate probit model with sample selection, but failure to reject the null hypothesis suggests the models could be estimated as individual probit regressions (Greene 2003; StataCorp 2011).

**Results**

***Comparison of Sample Means***

Comparison between adopters and non-adopters is found in Table 3.2. Analysis suggests that producers who adopted information technologies for VRT application of inputs were generally younger, more highly educated, and more likely to use computers for farm management. They were also less likely to own livestock, farmed larger cotton areas, were more likely to use irrigation, and more likely to grow picker cotton rather than stripper cotton. Adopters were also more likely to use each of the evaluated sources of precision farming information except other farmers, and were less likely to not use any of the information sources.

Results of the comparison between sub-populations of farmers who perceived fertilizer use to increase, not change, and decrease can be found in Table 3.3. Farmers who perceived fertilizer use not to change were more highly educated than those who perceived increased or decreased fertilizer use. Farmers who perceived fertilizer use to decrease farmed significantly larger cotton areas. Farmers who perceived fertilizer to not change or decrease were significantly more likely to use a picker than those who perceived an increase in input use. Farmers who perceived no change in fertilizer use were also significantly more likely to use University Extension as a source of precision farming information than those who perceived an increase or a decrease.

***Model Evaluation***

Multicollinearity diagnostics for the independent variables in both equations (12) and (13) were estimated. All independent variables in equation (12), with the exception of PICKER, ERS6, ERS7, and ERS9, had VIFs below two. While the VIFs of PICKER, ERS6, ERS7, and ERS9 were still below the threshold of 10, they were slightly higher than the other independent variables given expected correlation between PICKER and regional variables caused by regional differences in picker and stripper cotton. Multicollinearity diagnostics for equation (13) found VIFs of all independent variables to be below two. Therefore, the standard errors of the models did not appear to be adversely affected by multicollinearity.

The null hypothesis that $\rho$ was zero could not be rejected at any conventional level for the three bivariate probit models with sample selection for directional changes in fertilizer use equations (Table 3.4). Thus, it is appropriate to estimate individual binomial probit models for the adoption equation and each of the three models for directional changes in fertilizer use. a likelihood ratio test suggested that the overall adoption model was significant at the 1% level, and correctly predicted 1,047 (87%) of the adoption responses (Table 3.5). The models for a perceived increase, no change, and decrease in fertilizer use were all significant at the 1% level based on the results of likelihood ratio tests; correctly predicting 79 (80%), 84 (85%), and 66 (67%) of the responses, respectively (Tables 3.6, 3.7, and 3.8).

***Information Technology Adoption***

Results from the estimation of the adoption equation can be seen in Table 3.5. Cotton area (COTAREA) and the percentage of cotton area owned (OWNRENT) significantly influenced the probability that a farmer would adopt one or more of the select information technologies for VRT application of inputs. The use of other farmers (OFRMER) and trade shows (TRDESHW) as sources of precision farming information and not using any of the selected information sources (NOINFO) also significantly affected the adoption decision. Lastly, all regional dummy variables (ERS1, ERS4, ERS5, ERS6, ERS7, and ERS9) were associated with the decision to adopt precision agriculture technologies considered. Other explanatory variables in the adoption model were not significant.

Results for statistically significant farm decision maker and farm operation effects all exhibited the expected relationships. For each additional 405 hectares of cotton planted, the probability of a farmer adopting one or more information technologies for VRT increased 1.8%, holding all other variables at their means. For each 1% increase in the contribution of owned cotton area to total cotton area, farmers were 4.6% more likely to adopt.

Results also suggest interesting findings concerning the effects of farmer sources of precision farming information on adoption. Farmers who used trade shows as a source of precision farming information were 4.5% more likely to adopt one or more information technologies for VRT, holding all other variables at their means. The large variety of vendors present at trade shows likely offer farmers with an enhanced perspective of information technologies encouraging them to consider the technology or technologies that best suit their needs. Any technology manufacturers not currently using trade shows as a mode of promotion may reconsider this decision given these findings. Farmers who used other farmers as a source of precision farming information were 4.9% less likely to adopt than those who did not. Of the information sources included in this study, farmers obviously relate best to other farmers making them one of the most widely used sources of precision farming information (Velandia et al. 2011). Given the relatively slow adoption of precision farming among cotton farmers, it may be that hesitancy to adopt was perhaps shared among farmers. A farmer who did not use any of the information technologies analyzed was 8.9% less likely to adopt, holding all other variables at their means. As expected, the use of one or more of the sources of precision farming information significantly increased the probability that a farmer would adopt information technologies.

The negative relationship between each of the regional dummy variables and the adoption decision identified an overall propensity by farmers to be less likely to adopt independent of their location. Evaluating the marginal effects, farmers probability of adopting one or more information technologies for VRT decreased by somewhere between 7.7% and 12.7% depending on region, except for farmers in the Prairie Gateway who were 22.7% less likely to adopt than farmers in other regions.

***Perceived Increase in Fertilizer Use***

The use of a computer for farm management (COMP) and growing picker cotton (PICKER) significantly influenced the probability of a farmer perceiving an increase in fertilizer use (Table 3.6). Other explanatory variables in the equation for farmer perceptions that fertilizer use input use increased following VRT were not significant.

Results for all statistically significant farmer and farm effects carried their expected signs. Farmers who used a computer for farm management were 23.2% more likely to perceive fertilizer use to increase following VRT application, holding all other variables at their means. Familiarity with a computer likely facilitates more efficient use of collected data, leading to increased fertilizer productivity. Farmers who grew picker cotton were 67.6% less likely to perceive fertilizer use to increase. Excess nitrogen in cotton often reduces yield and fiber quality because of excessive vegetative growth. Thus, in higher-valued picker cotton production, farmers often avoid over application of fertilizer to avoid discounts for lint quality and the need for greater quantities of plant growth regulators and harvest aids prior to harvest.

***Perceived No Change in Fertilizer Use***

Age of the primary decision maker (AGE), holding a Bachelor's degree (EDUC), the use of a computer for farm management (COMP), cotton area (COTAREA), percentage of cotton area owned (OWNRENT), and the use of irrigation (IRRIG) contributed significantly to the perception that fertilizer use did not change following adoption (Table 3.7). The use of farm dealers (FRMDLER) and University Extension (EXTEN) as sources of precision farming information also contributed significantly to the perception that fertilizer use did not change following technology adoption. Other explanatory variables in the equation for farmer perceptions that fertilizer use did not change following VRT were not significant.

Results for statistically significant farm decision maker and farm operation effects exhibited the expected signs, except the variables for education and cotton area. For each additional 10 years in age, a farmer was 5.2% less likely to perceive fertilizer use to not change, holding all other variables at their means. It may be that younger farmers lack the experience necessary to recognize changes in input use. The probability of perceiving no change in input use was 16.6% higher for farmers who had a Bachelor's degree or higher. These farmers were hypothesized to have the analytical ability needed to recognize increases or decreases in fertilizer use, however it may be that their higher level of analytical ability actually helped them understand that fertilizer use would change differently in different parts of their fields, but overall would not change but become more efficient. Farmers who used a computer for farm management were 39% less likely to perceive no change in fertilizer use.

Contrary to the hypothesis that larger cotton area may be associated with farmers being more likely to perceive increased or decreased fertilizer use, each additional 405 hectares of cotton planted was associated with an increase in the probability of a farmer perceiving no change in fertilizer use by 3.3%, holding all other variables at their means. It may be that while farmers with more cotton area observed increases and decreases in fertilizer use in different sections of their fields, their overall input use did not change. For each 1% increase in the contribution of owned cotton area to total cotton area, farmers were 14.5% more likely to perceive no change in fertilizer use. Owning more of their land, farmers are expected to know more about in-field variability prior to adoption than farmers who rent more of their cotton area. Given the interaction between irrigation and fertilizer, the presence of irrigation likely decreased the probability of a farmer perceiving fertilizer use to remain idle. For example, farmers using irrigation were 10.6% less likely to perceive fertilizer use to not change than those who did not.

A farmer who used farm dealers as a source of precision farming information was 8.4% more likely to perceive no change in fertilizer use holding all other variables at their means. A farmer who used University Extension as a source of precision farming information was 19.8% more likely to perceive fertilizer use not to change. Farmers have been previously characterized to associate Extension as an unbiased source of information which may potentially lead to a more equable deduction of their perception of how the use of information technologies affected their fertilizer use (Larson et al. 2008).

*Perceived Decrease in Fertilizer Use*

The percentage of cotton area owned (OWNRENT) and growing picker cotton (PICKER) contributed significantly to the perception that fertilizer use decreased following adoption (Table 3.8). Also, the use of University Extension (EXTEN) as a source of precision farming information contributed significantly to the perception that fertilizer use decreased. Other explanatory variables in the equation for farmer perceptions that fertilizer use decreased following VRT were not significant.

Results for all statistically significant farmer and farm effects had their hypothesized signs. For each 1% increase in the contribution of owned cotton area to total cotton area, farmers were 35.3% less likely to perceive a decrease in fertilizer use, holding all other variables at their means. Farmers who grew picker cotton were 45% more likely to perceive fertilizer use to decrease than those who grew stripper cotton. Farmers who grew picker cotton may have used information technologies and VRT to manage soil fertility. Excess nitrogen in cotton may reduce yield and fiber quality through excessive vegetative growth. In higher-valued, picker cotton production, more efficient use of fertilizers such as nitrogen may also reduce the need for plant growth regulator and harvest aids because of excessive vegetative growth in the crop.

Farmers who used University Extension as a source of precision farming information were 35.4% less likely to perceive fertilizer use to decrease than those who did not. University Extension generates information for a wide range of farmers in a particular region as opposed to other sources of precision farming information which may provide a farmer with detailed information customized for their particular operation (Velandia et al. 2011). Thus, the more general information provided to farmers using University Extension as a source of precision farming information may lead to a lower probability of realizing fertilizer use to decrease.

## Summary and Conclusions

Farmer decisions to adopt one or more selected information technologies for VRT application of inputs and the subsequent effect of adoption on perceptions of directional changes in overall fertilizer use were analyzed as a function of observable farmer and farm characteristics, sources of precision farming information, and regional variables for farm location. Because adoption is a prerequisite to perceptions of directional changes in input use with VRT, data from the 2009 Southern Cotton Precision Farming Survey were analyzed using probit models with sample selection. Statistical modeling found no evidence of sample selection bias, and thus the adoption and changes in fertilizer use models were estimated as individual binomial probit models.

Results from the estimation of the adoption equation found that cotton growers who farmed more cotton and owned a larger portion of their farm operation were more likely to adopt selected information technologies for VRT application of inputs. By targeting these farmers, institutions developing and promoting information technologies may be more likely to successfully reach cotton growers who are likely to adopt the technologies considered. Results also indicated farmers using trade shows as a source of precision farming information were more likely to adopt. Thus, retailers of information technologies not currently using trade shows as a means of promoting their products may reconsider given these findings.

Subsequently, the factors influencing farmer perceptions of increased, unchanged, and decreased overall fertilizer use were evaluated individually for those farmers who chose to adopt one or more of the selected information technologies for VRT. Examining the results of the three equations simultaneously, several key findings were found to be associated with these perceptions. Cotton farmers in the sample who rented more of their cotton area and used picker rather than stripper harvest technology were more likely to perceive that overall fertilizer use declined with the use of the selected information technologies and VRT. This result may be explained by the desire of farmers growing higher value picker cotton to avoid excess nitrogen in cotton that may reduce yields, diminish fiber quality, and increase the need for plant growth regulators and harvest aids prior to harvest because of excessive vegetative growth. Thus, this result and other key findings of this research may not only be of interest to other cotton farmers but also to the USDA Natural Resource Conservation Service, who may be interested in the environmental impacts of decreased fertilizer use among cotton farmers. Results also suggest that cotton farmers who used University Extension or farm dealers as a source of precision farming information were more likely to perceive that overall fertilizer use did not change. Institutions involved in the education and promotion of precision farming may not only be interested in how farmers utilizing their information perceive VRT management to effect fertilizer use, but also in the other factors affecting these perceptions in order to tailor their efforts to reach farmers who are more likely to realize the economic and environmental benefits of precision agriculture.

Finally, the results this research lay the groundwork for future research to build upon regarding directional changes in fertilizer use, as well as the use of other inputs. Results of this research are limited by the evaluation of only a small sub-sample of selected precision farming technologies and only changes in overall fertilizer use. However, using these findings, future studies may be able to better identify factors influencing farmer perceptions of changes in input use and their implications on the economic and environmental benefits of precision farming.

## References

Babcock, B.A., and G.R. Pautsch. 1998. Moving from Uniform to Variable Fertilizer Rates on Iowa Corn: Effects on Rates and Returns. *Journal of Agricultural and Resource Economics* 23(2): 385-400.

Baerenklau, K.A., and K.C. Knapp. 2007. Dynamics of Agricultural Technology Adoption: Age Structure, Reversibility, and Uncertainty. *American Journal of Agricultural Economics* 89(1): 190-201.

Batte, M.T. 2000. Factors Influencing the Profitability of Precision Farming Systems. *Journal of Soil and Water Conservation* 55(1): 12-18.

Batte, M.T., and M.W. Arnholt. 2003. Precision Farming Adoption and Use in Ohio: Case Studies of Six Leading-Edge Adopters. *Computers and Electronics in Agriculture* 38(2): 125-139.

Batte M.T., E. Jones, and G.D. Schnitkey. 1990. Computer Use by Ohio Commercial Farmers. *American Journal of Agricultural Economics* 72(4): 934-945.

Boman, R.K., J.D. Wanjura, M.S. Kelley, C. Ashbrook, and E.F. Hequet. 2011. Picker vs. Stripper Harvesting in the Texas High Plain: Agronomic Implications. Paper presented at the National Cotton Council Beltwide Cotton Conference, Atlanta, GA, 4-7, January.

Brooks, N.L. 2001. Characteristics and Production Costs of U.S. Cotton Farms. Washington DC: U.S. Department of Agriculture, Economic Research Service, Technical Bulletin No. 974-2.

Butler, J.S. 1996. *Estimating the Correlation in Censored Probit Models*. The MIT Press 78(2): 355-358.

Chatterjee, S., and B. Price. 1991. *Regression Analysis by Example*. New York: Wiley.

Cooper, J.E., and R.W. Keim. 1996. Incentive Payments to Encourage Farmer Adoption of Water Quality Protection Practices. *American Journal of Agricultural Economics* 78(1): 54-64.

Daberkow, S.G., and W.D. McBride. 1998. Socioeconomic Profiles of Early Adopters of Precision Agriculture Technologies. *Journal of Agribusiness* 16(2): 151-168.

Dillman, D.A. 1978. *Mail and Telephone Surveys*. New York: Wiley New York.

D'Souza, G., D. Cyphers, and T. Phipps. 1983. Factors Affecting the Adoption of Sustainable Agricultural Practices. *Agricultural and Resource Economics Review* 22(2): 159-165.

English, B.C., S.B. Mahajanashetti, and R.K. Roberts. 2001. Assessing Spatial Break-Even Variability in Fields with Two or More Management Zones. *Journal of Agricultural and Applied Economics* 33(3): 551-565.

Fritschi, F.B., B.A. Roberts, R.L. Travis, D.W. Rains, and R.B. Hutmacher. 2003. Response of Irrigated Acala and Pima Cotton to Nitrogen Fertilization: Growth, Dry Matter Partitioning, and Yield. *Agronomy Journal* 95(1): 133-166.

Gaylor, M.J., G.A. Buchanan, F.R. Gilliland, and R.L. Davis. 1983. Interactions Among a Herbicide Program, Nitrogen Fertilization, Tarnished Plant Bugs, and Planting Dates for Yield and Maturity of Cotton. *Agronomy Journal* 75(6): 903-907.

Greene, W.H. 2003. *Econometric Analysis*. Upper Saddle River: Prentice Hall.

Griffin, T.W., J. Lowenberg-DeBoer, D.M. Lambert, J. Peone, T. Payne, and S.G. Daberkow. 2004. Adoption, Profitability, and Making Better Use of Precision Farming Data. Purdue University Dept. Agr. Econ. Staff Paper #04-06.

Harper, D.C., D.M. Lambert, R.K. Roberts, B.C. English, M. Velandia, J.A. Larson, D.F. Mooney, S.L. Larkin, and J.M. Reeves. 2011. Paper presented at the 10th International Conference on Precision Agriculture, Denver, CO, 18-21, July.

Heckman, J.J. 1979. Sample Selection Bias as a Specification Error. *Econometrica* 47(1): 153-161.

Howard, D.D., C.O. Gwathmey, M.E. Essington, R.K. Roberts, and M.D. Mullen. 2001. Nitrogen Fertilization of No-Till Cotton on Loess-Derived Soils. *Agronomy Journal* 93(1): 157-163.

Khanna, M. 2001. Sequential Adoption of Site-Specific Technologies and Its Implications for Nitrogen Productivity: A Double Selectivity Model. *American Journal of Agricultural Economics* 83(1): 35-51.

Kohli, S.E., and L.G. Morrill. 1976. Influence of Nitrogen, Narrow Rows, and Plant Population on Cotton Yield and Growth. *Agronomy Journal* 68(6): 897-901.

Kotsiri, S., R. Rejesus, M. Marra, and M. Velandia. 2011. Farmers' Perceptions about Spatial Yield Variability and Precision Farming Technology Adoption: An Empirical Study of Cotton Production in 12 Southern States. Paper presented at the Southern Agricultural Economics Association annual meeting, Corpus Christi, TX, 5-8 February.

Lambert, D.M., and J. Lowenberg-DeBoer. 2000. *Precision Agriculture Profitability Review*. Site-Specific Management Center, School of Agriculture, Purdue University.

Lambert, D.M., J. Lowenberg-DeBoer, and G.L. Malzer. 2006. Economic Analysis of Spatial-Temporal Patterns in Corn and Soybean Response to Nitrogen and Phosphorus. *Agronomy Journal* 98(1): 43-54.

Lambert, D.M., P. Sullivan, R. Claassen, L. Foreman. 2007. Profiles of US Farm Households Adopting Conservation-Compatible Practices. *Land Use Policy* 24(1): 72-88.

Larkin, S.L., L. Perruso, M.C. Marra, R.K. Roberts, B.C. English, J.A. Larson, R.L. Cochran, and S.W. Martin. 2005. Factors Affecting Perceived Improvements in Environmental Quality from Precision Farming. *Journal of Applied Economics* 37(3): 577-588.

Larson, J.A., R.K. Roberts, B.C. English, S.L. Larkin, M.C. Marra, S.W. Martin, K.W. Paxton, and J.M. Reeves. 2008. Factors Affecting Farmer Adoption of Remotely Sensed Imagery for Precision management in Cotton Production. *Precision Agriculture* 9(4):195-208.

Larson, J.A., C.O. Gwathmey, R.K. Roberts, and R.M. Hayes. 2004. Effects of Plant Population Density on Net Revenues from Ultra-Narrow-Row Cotton. *Journal of Cotton Science* 8(1): 69-82.

Lohr, S.L. 1999. *Sampling: Design and Analysis*. Pacific Grove: Brooks/Cole.

Marra, M.C., R.M. Rejesus, R.K. Roberts, B.C. English, J.A. Larson, S.L. Larkin, and S. Martin. 2010. Estimating the Demand and Willingness-to-pay for Cotton Yield Monitors. *Precision Agriculture* 11(3): 215-238.

Miranda, A., and S. Rabe-Hesketh. 2006. Maximum Likelihood Estimation of Endogenous Switching and Sample Selection Models for Binary, Ordinal, and Count Variables. *The Stata Journal* 6(3): 285-308.

Monks, C.D., G. Wehtje, C. Burmester, A.J. Price, M.G. Patterson, D.P Delaney, W. Faircloth, and M.R. Woods. 2007. Glyphosate-Resistant Cotton Response to Glyphosate Applied in Irrigated and Nonirrigated Conditions. *Weed Technology* 21(4): 915-921.

Mooney, D.F., R.K. Roberts, B.C. English, D.M. Lambert, J.A. Larson, M. Velandia, S.L. Larkin, M.C. Marra, S.W. Martin, A. Mishra, K.W. Paxton, R. Rejesus, E. Segarra,C.

Wang, and J.M. Reeves. 2010. Precision Farming by Cotton Producers in Twelve Southern States: Results from the 2009 Southern Cotton Precision Farming Survey. University of Tennessee Dept. Agr. and Res. Econ. Research Series 10-02.

Popp, J., and T. Griffin. 2000. Adoption Trends of Early Adopters of Precision Farming in Arkansas. Paper presented at the 5th International Conference on Precision Agriculture, Minneapolis, MN, 16-19, July.

Roberts, R.K., B.C. English, and J.A. Larson. 2006. The Variable-Rate Input Application Decision for Multiple Inputs with Interactions. *Journal of Agricultural and Resource Economics* 3(2): 391-413.

Roberts, R.K., B.C. English, and S.B. Mahajanashetti. 2000. Evaluating the Returns to Variable Rate Nitrogen Application. *Journal of Agricultural and Applied Economics* 31(1): 133-143.

Roberts, R.K., B.C. English, J.A. Larson, R.L. Cochran, W.R. Goodman, S.L. Larkin, M.C. Marra, S.W. Martin, W.D. Shurley, and J.M. Reeves. 2004. Adoption of Site-Specific Information and Variable Rate Technologies in Cotton Precision Farming. *Journal of Agricultural and Applied Economics* 36(1): 143-158.

Roberts, R.K., S.B. Mahajanashetti, B.C. English, J.A. Larson, D.D. Tyler. 2002. Variable Rate Nitrogen Application on Corn Fields: The Role of Spatial Variability and Weather. *Journal of Agricultural and Applied Economics* 34(1): 111-129.

StataCorp. 2011. *Stata Statistical Software: Release 12*. College Station, TX: StataCorp LP.

Surjandari, I., and M.T. Batte. 2003. Adoption of Variable Rate Technology. *Makara, Technolgi* 7(3): 119-124.

Swinton S.M., and Lowenberg-DeBoer. 1998. Evaluating the Profitability of Site-Specific Farming. *Journal of Production Agriculture* 11(4):439-446.

Torbett, J.C., R.K. Roberts, J.A. Larson, and B.C. English. 2007. Perceived Importance of Precision Farming Technologies in Improving Phosphorus and Potassium Efficiency in Cotton Production. *Precision Agriculture* 8(3): 127-137.

—. 2008. Perceived Improvements in Nitrogen Fertilizer Efficiency from Cotton Precision Farming. *Computers and Electronics in Agriculture* 64(2): 140-148.

U.S. Census Bureau. 2011. County Business Patterns. Available at http://www.census.gov/econ/cbp/index.html (accessed December 12, 2011).

U.S. Department of Agriculture, Economic Research Service (USDA-ERS). 2012. Briefing Room: ERS U.S. Farm Resource Regions. Available at http://www.ers.usda.gov/Briefing/ARMS/ResourceRegions/ResourceRegions.htm (accessed January 3, 2012).

—. 2011. Briefing Room: Farm Household Economics and Well-Being. Available at http://www.ers.usda.gov/Briefing/WellBeing/farmhouseincome.htm (accessed December 14, 2011).

Valco, T.D., W.S. Anthony, and D.D. McAlister III. 2001. Ultra Narrow Row Cotton Ginning and Textile Performance Results. Paper presented at the National Cotton Council Beltwide Cotton Conference, Anaheim, CA, 9-13, January.

Velandia, M., D.M. Lambert, M.P. Mendieta, R.K. Roberts, J.A. Larson, B.C. English, R.M. Rejesus, and A.K. Mishra. 2011. Factors Influencing Cotton Farmers' Perceptions about the Importance of Information Sources in Precision Farming Decisions. Paper presented at the Agricultural and Applies Economics Association's Annual Meeting, Pittsburgh, PA, 24-26, July.

Walton, J.C., D.M. Lambert, R.K. Roberts, J.A. Larson, B.C. English, S.L. Larkin, S.W. Martin, M.C. Marra, K.W. Paxton, and J.M. Reeves. 2008. Adoption and Abandonment of Precision Soil Sampling in Cotton Production. *Journal of Agricultural and Resource Economics* 33(3): 428-448.

Walton, J.C., J.A. Larson, R.K. Roberts, D.M. Lambert, B.C. English, S.L. Larkin, M.C. Marra, S.W. Martin, K.W. Paxton, and J.M. Reeves. 2010. Factors Influencing Farmer Adoption of Portable Computers for Site-Specific Management: A Case Study for Cotton Production. *Journal of Agricultural and Applied Economics* 42(2): 193-209.

Wang, D. T. Prato, Z. Qui, N.R. Kitchen, and K.A. Sudduth. 2003. Economic and Environmental Evaluation of Variable Rate Nitrogen and Lime Application for Claypen Soil Fields. *Precision Agriculture* 4(1): 35-52.

Watkins, K.B., Y.C. Lu, and W.Y. Huang. 1998. Economic and Environmental Feasibility of Variable Rate Nitrogen Fertilizer Applications with Carry-Over Effects. *Journal of Agricultural and Resource Economics* 23(4): 401-426.

# Appendix

## Appendix

17. For each variable rate cotton management decision in the left column of the table below, indicate the acres on which the five information gathering technologies were used to make the variable rate decision. Leave blanks where the technology was not used. (Provide your best estimate.)

| Variable Rate Decision | 1. Yield Monitoring with GPS | 2. Aerial/Satellite Infrared Imagery | 3. Handheld GPS Units | 4. Green Seeker | 5. Electrical Conductivity (for example, Veris, Soil Doctor) |
|---|---|---|---|---|---|
| | | | | | |
| Drainage | | | | | |
| Fertility or Lime | | | | | |
| Seeding | | | | | |
| Growth Regulator | | | | | |
| Harvest Aids | | | | | |
| Fungicide | | | | | |
| Herbicide | | | | | |
| Insecticide | | | | | |
| Irrigation | | | | | |

18. Did your input use change for the following inputs after you used variable rate technology on your cotton fields? Mark a "+" for an increase, "–" for a decrease, or "NC" for no change. Skip if you did not use variable rate technology.

| | Fertilizer | Lime | Seeds | Growth Regulator | Harvest Aids | Fungicide | Herbicide | Insecticide | Irrigation water |
|---|---|---|---|---|---|---|---|---|---|
| Indicate the direction of the change with a +, -, NC | | | | | | | | | |
| Indicate your best estimate of the percent change | | | | | | | | | |

**Figure 3.1.** Survey Questions Used in Collection of Information Technology Adoption and Percieved Input Use Analysis

**Table 3.1.** Variable Definitions, Hypothesized Signs, and Means in the Adoption and Directional Changes in Fertilizer Use Equations

| | | Hypothesized Signs | | | | |
|---|---|---|---|---|---|---|
| | | | Fertilizer Use | | | |
| Variable | Definition | Adoption | Increase | No Change | Decrease | Mean |
| **Farmer Characteristics** | | | | | | |
| *AGE* | Age in years of the primary decision maker | – | + | – | + | 55.98 |
| *EDUC* | Equals one if the farmer received a bachelor's degree or higher and zero otherwise | + | + | – | + | 0.40 |
| *INC* | Equals one if household income was over $100K and zero otherwise | + | +/– | +/– | +/– | 0.46 |
| *INCFRM* | Percentage of household income from farming operations | + | + | – | + | 0.68 |
| *COMP* | Equals one if the farmer used a computer for farm management and zero otherwise | + | + | – | + | 0.49 |
| **Farm Characteristics** | | | | | | |
| *LIVSTK* | Equals one if the farmer owned livestock and zero otherwise | – | n/a | n/a | n/a | 0.33 |
| *COTAREA* | Total cotton area (in 405 hectare units) | + | + | – | + | 0.58 |
| *OWNRENT* | Percentage of cotton area owned to cotton area planted | + | – | + | – | 0.38 |
| *IRRIG* | Equals one if the farmer used irrigation on their crop and zero otherwise | + | + | – | + | 0.44 |

**Table 3.1.** Continued

| Variables | Definition | Hypothesized Signs | | | | Mean |
|---|---|---|---|---|---|---|
| | | | Fertilizer Use | | | |
| | | Adoption | Increase | No Change | Decrease | |
| *PICKER* | Equals one if the farmer used a picker for harvesting cotton and zero otherwise | + | − | | + | 0.60 |
| *FRMSPLY* | Number of farm input suppliers at the county level | + | +/− | +/− | +/− | 8.35 |
| **Farmers' Sources of Precision Farming Information** | | | | | | |
| *FRMDLER* | Equals one if the farmer received precision farming information from farm dealers and zero otherwise | +/− | +/− | +/− | +/− | 0.56 |
| *CRPCSLT* | Equals one if the farmer received precision farming information from crop consultant and zero otherwise | +/− | +/− | +/− | +/− | 0.28 |
| *OFRMER* | Equals one if the farmer received precision farming information from other farmers and zero otherwise | +/− | +/− | +/− | +/− | 0.57 |
| *EXTEN* | Equals one if the farmer received precision farming information from extension and zero otherwise | +/− | +/− | +/− | +/− | 0.37 |
| *TRDSHW* | Equals one if the farmer received precision farming information from trade shows and zero otherwise | +/− | +/− | +/− | +/− | 0.30 |

**Table 3.1.** Continued

| Variables | Definition | Hypothesized Signs | | | | Mean |
|---|---|---|---|---|---|---|
| | | | Fertilizer Use | | | |
| | | Adoption | Increase | No Change | Decrease | |
| *INTER* | Equals one if the farmer received precision farming information from the internet and zero otherwise | +/– | +/– | +/– | +/– | 0.22 |
| *MEDIA* | Equals one if the farmer received precision farming information from news or media outlets and zero otherwise | +/– | +/– | +/– | +/– | 0.33 |
| *NOINFO* | Equals one if the farmer did not indicate the use of any of the included information sources and zero otherwise | – | n/a | n/a | n/a | 0.16 |
| **Location Variables** | | | | | | |
| *ERS1* | Equals one if the farm was located in the Heartland Region and zero otherwise | +/– | n/a | n/a | n/a | 0.03 |
| *ERS5* | Equals one if the farm was located in the Eastern Uplands and zero otherwise | +/– | n/a | n/a | n/a | 0.40 |
| *ERS4* | Equals one if the farm was located in the Prairie Gateway and zero otherwise | +/– | n/a | n/a | n/a | 0.03 |
| *ERS6* | Equals one if the farm was located in the Southern Seaboard and zero otherwise | +/– | n/a | n/a | n/a | 0.28 |
| *ERS7* | Equals one if the farm was located in the Fruitful Rim and zero otherwise | +/– | n/a | n/a | n/a | 0.08 |

**Table 3.1.** Continued

| Variable | Definition | Hypothesized Signs | | | | Mean |
|---|---|---|---|---|---|---|
| | | | Fertilizer Use | | | |
| | | Adoption | Increase | No Change | Decrease | |
| *ERS9* | Equals one if the farm was located in the Mississippi Portal and zero otherwise | +/− | n/a | n/a | n/a | 0.17 |

**Table 3.2.** Comparisons of Characteristics between Adopters and Non-Adopters of One or More Information Technologies Used for Variable Rate Technology Application of Inputs in Cotton Production

| Variables[a] | Adopter Weighted Mean[b] | Non-Adopter Weighted Mean | *t*-value[cd] |
|---|---|---|---|
| *AGE* | 51.50 | 56.60 | −3.50*** |
| *EDUC* | 0.53 | 0.38 | 3.04*** |
| *INC* | 0.50 | 0.46 | 0.90 |
| *INCFRM* | 0.71 | 0.67 | 1.43 |
| *COMP* | 0.70 | 0.46 | 5.11*** |
| *LIVSTK* | 0.25 | 0.34 | −2.22** |
| *COTAREA* | 0.80 | 0.55 | 3.09*** |
| *OWNRENT* | 0.38 | 0.38 | 0.17 |
| *IRRIG* | 0.53 | 0.42 | 2.24** |
| *PICKER* | 0.77 | 0.58 | 4.36*** |
| *FRMSPLY* | 7.67 | 8.45 | −1.16 |
| *FRMDLER* | 0.76 | 0.53 | 5.47*** |
| *CRPCSLT* | 0.42 | 0.27 | 3.47*** |
| *OFRMER* | 0.61 | 0.57 | 0.81 |
| *EXTEN* | 0.45 | 0.36 | 1.95* |
| *TRDSHW* | 0.51 | 0.28 | 4.87*** |
| *INTER* | 0.41 | 0.20 | 4.82*** |
| *MEDIA* | 0.47 | 0.32 | 3.14*** |
| *NOINFO* | 0.01 | 0.18 | −9.94*** |
| | | | |
| n | 161 | 1,043 | |
| Expanded Population | 1,545 | 11,096 | |

[a]Variables are defined in Table 1.
[b]An adopter was defined as having one or more of the following information technologies: yield monitor, passive remote sensing, personal digital assistant (PDA) or handheld global positioning system (GPS) devices, active remote sensing, and electrical conductivity.
[c]Results of side-by-side *t*-tests between the weighted means of adopters and non-adopters
[d]Significance at the 1%, 5%, and 10% levels denoted by ***, **, and * respectively.

**Table 3.3.** Comparisons of Characteristics between Perceptions of Directional Changes in Fertilizer Use Following the Adoption of One or More Information Technologies for Variable Rate Technology Application of Inputs in Cotton Production

| Variables[a] | Fertilizer Increase Weighted Mean[b] | Fertilizer No Change Weighted Mean | Fertilizer Decrease Weighted Mean |
|---|---|---|---|
| *AGE* | 53.36 a | 50.26 a | 49.22 a |
| *EDUC* | 0.44 a | 0.82 b | 0.61 a |
| *INC* | 0.63 a | 0.34 a | 0.55 a |
| *INCFRM* | 0.75 a | 0.65 a | 0.74 a |
| *COMP* | 0.77 a | 0.64 a | 0.84 a |
| *COTAREA* | 0.60 a | 0.76 a | 1.07 b |
| *OWNRENT* | 0.52 a | 0.53 a | 0.29 a |
| *IRRIG* | 0.66 a | 0.30 b | 0.54 a |
| *PICKER* | 0.58 a | 0.92 b | 0.95 b |
| *FRMSPLY* | 9.91 a | 7.32 a | 6.61 a |
| *FRMDLER* | 0.75 a | 0.82 a | 0.79 a |
| *CRPCOSLT* | 0.47 a | 0.42 a | 0.50 a |
| *OFRMER* | 0.45 a | 0.61 a | 0.67 a |
| *EXTEN* | 0.41 a | 0.85 b | 0.41 a |
| *TRDESHW* | 0.53 a | 0.51 a | 0.56 a |
| *INTER* | 0.34 a | 0.63 a | 0.38 a |
| *MEDIA* | 0.54 a | 0.48 a | 0.52 a |
| | | | |
| n | 25 | 18 | 56 |
| Expanded Population | 275 | 191 | 465 |

[a]Variables are defined in Table 1.

[b]Means followed by the same letter in each row are not statistically different at the 0.05 level.

**Table 3.4.** Wald Tests of Independent Equations

| Model | $\rho^a$ | $\chi^2$ Statistic[b] | p-value |
|---|---|---|---|
| Fertilizer Increased | 0.116 | 0.10 | 0.755 |
| Fertilizer No Change | −0.626 | 0.88 | 0.348 |
| Fertilizer Decreased | −0.603 | 1.51 | 0.219 |

[a]Correlation between the error terms $e_i$ and $e_j$ of equations (13) and (14).
[b] $\chi^2$ Statistic for the null hypothesis that $\rho$=0.

**Table 3.5.** Results from Estimation of the Adoption of One or More Information Technologies for Variable Rate Technology Equation

| | Dependent Variable | |
|---|---|---|
| | *ADOPT*[a] | |
| Independent Variable[b] | Probit Coefficient[c] | Marginal Effect |
| *AGE* | –0.008 | –0.001 |
| *EDUC* | 0.159 | 0.024 |
| *INC* | –0.122 | –0.018 |
| *INCFRM* | 0.251 | 0.037 |
| *COMP* | 0.178 | 0.026 |
| *LIVSTK* | –0.158 | –0.023 |
| *COTAREA* | 0.121** | 0.018** |
| *OWNRENT* | 0.310* | 0.046* |
| *IRRIG* | 0.158 | 0.024 |
| *PICKER* | –0.036 | –0.005 |
| *FRMSPLY* | –0.004 | –0.001 |
| *FRMDLER* | 0.210 | 0.031 |
| *CRPCSLT* | 0.109 | 0.017 |
| *OFRMER* | –0.319** | –0.049** |
| *EXTEN* | –0.178 | –0.025 |
| *TRDSHW* | 0.281** | 0.045* |
| *INTER* | 0.245 | 0.040 |
| *MEDIA* | 0.178 | 0.027 |
| *NOINFO* | –0.929*** | –0.089*** |
| *ERS1* | –1.090** | –0.077*** |
| *ERS4* | –1.704*** | –0.227*** |
| *ERS5* | –1.381** | –0.082*** |
| *ERS6* | –1.151*** | –0.127*** |
| *ERS7* | –1.322*** | –0.093*** |
| *ERS9* | –0.830* | –0.085** |
| | | |
| n | 1,204 | |
| Expanded Population | 12,641 | |
| Unrestricted Log-likelihood | –3,927.31 | |
| Restricted Log-likelihood | –4,694.14 | |
| Likelihood Ratio Statistic[d] | 1,533.67*** | |
| Correctly Predicted | 1,047(87%) | |

[a]*ADOPT* equals one if the farmer adopted one or more information technologies (yield monitor, passive remote sensing, personal digital assistant or handheld global positioning system devices, active remote sensing, and electrical conductivity) for variable rate technology application and zero otherwise.
[b]Independent Variables are defined in Table1.
[c]Significance at the 1%, 5%, and 10% levels denoted by ***, **, and * respectively.
[d]Likelihood ratio statistic is LR = 2(log-likelihood unrestricted – log-likelihood restricted).

**Table 3.6.** Results from Estimated Equation of Farmer Perceptions of Increased Fertilizer Use with Variable Rate Technology in Cotton Production

| | Dependent Variable | |
|---|---|---|
| | *FERTILIZER INCREASE*[a] | |
| Independent Variable[b] | Probit Coefficient[c] | Marginal Effect |
| *AGE* | 0.010 | 0.003 |
| *EDUC* | –0.575 | –0.187 |
| *INC* | 0.323 | 0.101 |
| *INCFRM* | 0.280 | 0.088 |
| *COMP* | 0.907** | 0.232** |
| *COTAREA* | –0.260 | –0.082 |
| *OWNRENT* | –0.138 | –0.044 |
| *IRRIG* | 0.569 | 0.176 |
| *PICKER* | –1.974*** | –0.676*** |
| *FRMSPLY* | 0.006 | 0.002 |
| *FRMDLER* | 0.039 | 0.012 |
| *CRPCSLT* | 0.158 | 0.050 |
| *OFRMER* | –0.564 | –0.182 |
| *EXTEN* | 0.334 | 0.105 |
| *TRDSHW* | –0.249 | –0.079 |
| *INTER* | –0.268 | –0.083 |
| *MEDIA* | –0.074 | –0.023 |
| | | |
| n | 99 | |
| Expanded Population | 931 | |
| Unrestricted Log-likelihood | –394.72 | |
| Restricted Log-likelihood | –565.34 | |
| Likelihood Ratio Statistic[d] | 341.24*** | |
| Correctly Predicted | 79(80%) | |

[a]*FERTILIZER IFNCREASE* equals one if the farmer perceived fertilizer use to increase and zero otherwise.
[b]Independent Variables are defined in Table1.
[c]Significance at the 1%, 5%, and 10% levels denoted by ***, **, and * respectively.
[d]Likelihood ratio statistic is LR = 2(log-likelihood unrestricted – log-likelihood restricted).

**Table 3.7.** Results from Estimated Equation of Farmer Perceptions of No Change in Fertilizer Use with Variable Rate Technology in Cotton Production

| | Dependent Variable | |
|---|---|---|
| | *FERTILIZER NOCHANGE*[a] | |
| Independent Variable[b] | Probit Coefficient[c] | Marginal Effect |
| *AGE* | –0.049*** | –0.005** |
| *EDUC* | 1.687*** | 0.166*** |
| *INC* | –0.360 | –0.039 |
| *INCFRM* | –0.656 | –0.070 |
| *COMP* | –1.802*** | –0.390*** |
| *COTAREA* | 0.312* | 0.033 |
| *OWNRENT* | 1.359** | 0.145* |
| *IRRIG* | –0.909** | –0.106* |
| *PICKER* | 0.267 | 0.025 |
| *FRMSPLY* | –0.006 | –0.001 |
| *FRMDLER* | 1.259** | 0.084** |
| *CRPCSLT* | –0.652 | –0.070 |
| *OFRMER* | 0.216 | 0.022 |
| *EXTEN* | 1.602*** | 0.198*** |
| *TRDSHW* | –0.598 | –0.068 |
| *INTER* | 0.405 | 0.046 |
| *MEDIA* | –0.187 | –0.020 |
| | | |
| n | 99 | |
| Expanded Population | 931 | |
| Unrestricted Log-likelihood | –263.92 | |
| Restricted Log-likelihood | –472.10 | |
| Likelihood Ratio Statistic[d] | 416.36*** | |
| Correctly Predicted | 84(85%) | |

[a]*FERTILIZER NOCHANGE* equals one if the farmer perceived fertilizer use to not change and zero otherwise.
[b]Independent Variables are defined in Table1.
[c]Significance at the 1%, 5%, and 10% levels denoted by ***, **, and * respectively.
[d]Likelihood ratio statistic is LR = 2(log-likelihood unrestricted – log-likelihood restricted).

**Table 3.8.** Results from Estimated Equation of Farmer Perceptions of Decreased Fertilizer Use with Variable Rate Technology in Cotton Production

| | Dependent Variable | |
|---|---|---|
| | *FERTILIZER DECREASE*[a] | |
| Independent Variable[b] | Probit Coefficient[c] | Marginal Effect |
| *AGE* | –0.006 | –0.002 |
| *EDUC* | –0.167 | –0.067 |
| *INC* | 0.114 | 0.045 |
| *INCFRM* | 0.008 | 0.003 |
| *COMP* | –0.076 | –0.030 |
| *COTAREA* | 0.115 | 0.046 |
| *OWNRENT* | –0.885** | –0.353** |
| *IRRIG* | –0.237 | –0.094 |
| *PICKER* | 1.333*** | 0.450*** |
| *FRMSPLY* | –0.025 | –0.010 |
| *FRMDLER* | –0.390 | –0.154 |
| *CRPCSLT* | 0.315 | 0.125 |
| *OFRMER* | 0.368 | 0.146 |
| *EXTEN* | –0.918** | –0.354*** |
| *TRDSHW* | 0.352 | 0.139 |
| *INTER* | –0.419 | –0.166 |
| *MEDIA* | 0.412 | 0.163 |
| | | |
| n | 99 | |
| Expanded Population | 931 | |
| Unrestricted Log-likelihood | –494.09 | |
| Restricted Log-likelihood | –645.37 | |
| Likelihood Ratio Statistic[d] | 302.56*** | |
| Correctly Predicted | 66(67%) | |

[a]*FERTILIZER DECREASE* equals one if the farmer perceived fertilizer use to decrease and zero otherwise.
[b]Independent Variables are defined in Table1.
[c]Significance at the 1%, 5%, and 10% levels denoted by ***, **, and * respectively.
[d]Likelihood ratio statistic is LR = 2(log-likelihood unrestricted – log-likelihood restricted).

# Chapter 4: Summary

**Summary**

This thesis evaluated potential impacts of agricultural technology on input use in soybean and cotton production. This research was motivated by rising prices of inputs used in crop production and their effect on farmer production decisions. Included are a reevaluation of currently used production practices and the adoption of new technologies. Findings of this research may be useful to farmers and industry professionals interested in production practices that will generate the highest profit and how these decisions impact input use.

The first study of this thesis focused on estimating economically optimal plant population density (EOPPD) considering seeding rate, MG, RS, and input-output prices in the rolling uplands region of the Midsouth for dryland soybean production. Because farmers are unsure of future weather conditions when they make their planting decisions, they must make these decisions based on expected weather conditions. Hence, response functions were weighted by year based on the Ångström weather index to calibrate original response functions to average weather conditions. Evaluation of weighted average response functions suggested that MG IV soybean cultivars planted in narrow RS at seeding rates necessary to achieve final PPD of 115,000 plants ha$^{-1}$ generated the highest net returns. These findings support the hypothesis of economic benefits of narrow RS, but fail to support the benefits of planting earlier maturing MG III soybean cultivars to avoid late season drought.

Limitations of this study include the mid-May planting date used for all three of the MG evaluated. Previous research has shown benefits to using earlier planting dates when utilizing earlier maturing soybean cultivars. Modeling the potential influence of planting dates on the economically optimal production system was beyond the scope of this study. However, data for alternative planting dates are available for this production region, and are an objective of future research to determine how this may affect farmer production decisions including PPD, MG, and RS.

The second portion of this research focused on the factors that influence farmers' decisions to adopt information technologies for VRT application of inputs and subsequent perceptions of directional changes in overall fertilizer use. These decisions were hypothesized to be influenced by farmer and farm characteristics, sources of precision farming information, and regional variables. Results from a probit analysis indicated that the probability of adopting one or more information technologies for VRT application of inputs was higher for farmers who farmed a larger area of cotton, owned a larger portion of the land they farmed, and used trade shows as a source of precision farming. By targeting these farmers, entities developing and promoting information technologies may be more likely to successfully reach cotton growers who are most likely to adopt.

Subsequently, the factors influencing farmer perceptions of increased, unchanged, and decreased overall fertilizer use were evaluated individually for those farmers who chose to adopt one or more of the selected information technologies for VRT. Cotton farmers in the sample who rented more of their cotton area and used picker rather than stripper harvest technology were more likely to perceive that overall fertilizer use declined with the use of the selected information technologies and VRT. Results also suggest that cotton farmers who used University Extension or farm dealers as a source of precision farming information were more likely to perceive that overall fertilizer use did not change. Thus, the results of this research may not only be of interest to other cotton farmers but also to the USDA Natural Resource Conservation Service, who may be interested in the environmental impacts of decreased fertilizer use among cotton farmers, and institutions involved in the education and promotion of precision farming, who may be able to tailor their efforts to reach farmers who are more likely to realize the economic and environmental benefits of precision agriculture.

Finally, the results this research lay the groundwork for future research to build upon regarding directional changes in fertilizer use, as well as the use of other inputs. Results of this research are limited by the evaluation of only small sub-sample of selected precision farming technologies and only changes in overall fertilizer use. However, using these findings, future studies may be able to better identify factors influencing farmer perceptions of changes in input use and their implications on the economic and environmental benefits of precision farming.

**Vita**

Nathanael Thompson was born on April 25, 1989 in Venus, FL to Kerry and Lori Thompson. He graduated with honors from Lake Placid High School in 2007. He then attended South Florida Community College where he completed his Associates of Arts degree in one year. Next, Nathanael attended the University of South Florida where he completed his Bachelor's of Science degree in Economics. After completion of his undergraduate degree, Nathanael attended the University of Tennessee where he completed a Master's of Science degree in Agricultural Economics. He has now accepted an offer to pursue his Doctorate of Philosophy in Agricultural Economics from Oklahoma State University.